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ABSTRACT

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 increases employment by augmenting the number of care workers and nurses on flexible employment contracts, and decreases difficulty in staff retention. Robot adoption also reduces the monthly wages of regular nurses, consistent with reduced burden of care. Our findings suggest that the impact of robots may not be detrimental to labor and may remedy challenges posed by rapidly aging populations.

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A data appendix is available at http://www.nber.org/data-appendix/w28322

1. Introduction

A wave of new technologies – such as robotics, artificial intelligence, digital platforms, and big data analytics – have prompted increasing concern about a substantial and negative impact on labor markets in the coming decades (Brynjolfsson and McAfee 2014). These technologies raise uncertainties about employment, wages, productivity, and inequality, and sustainability of high living standards. According to some narratives, a dystopian future looms, with robots displacing humans through ongoing relentless automation. Against the backdrop of stagnant median real wages, long-term structural changes, and outsourcing under globalization compounded by the unequal impacts of crises, it is not surprising that bleak prospects for the future of meaningful work contribute to "deaths of despair" (Case and Deaton 2020).

Yet automation also holds promise for addressing some labor market challenges. Demographers warn of the potential negative economic impacts of rising old-age dependency ratios and declining employment-to-population ratios in the US (Abraham and Kearney 2020) and many other high-income countries, prompting policies to support fertility, promote longer working lives, and adapt labor tasks for older workers.[1] In many high-income countries far along in the demographic transition, robots are increasingly being adopted to remedy these challenges posed by rapidly aging populations, both in terms of augmenting a declining working-age population and meeting demand for services from a growing elderly population. Indeed, development and diffusion of robotics and automation technologies can be linked to if not driven by demography (Acemoglu and Restrepo 2018, Prettner and Bloom 2020). Evidence from Japan and other OECD countries with older population age structures than that of the US shows that demographic factors account for a large part of variation in industrial robotics adoption (Acemoglu and Restrepo 2018). In the US, the projected reduction in labor supply from demographic change may outweigh the reduction in demand from automation for a decade or longer, Varian (2020) argues.

The research question we address in this paper is how adoption of robots affects workers in the service sector. We contribute to the literature in two ways. First, the rapidly growing literature on the impact of robots on labor markets has almost entirely focused on the manufacturing sector (e.g., Acemoglu and Restrepo 2020; Dauth et al. 2017; Dixen et al.

[1] See Bloom and Prettner (2020) for a recent review.

2019; Bessen et al. 2019),[2] but very few have examined the service sector.[3] This is an important omission because, as we discuss below, robots may play substantially different roles in the service sector especially in a tight labor market. As far as we are aware, our paper is the first to rigorously examine the impact of robots on jobs in the service sector. 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 effect of robot adoption, similar to other on-going research that uses establishment- or firm-level robot adoption data in the manufacturing sector (Acemoglu et al. 2020; Lee and Lee 2020; Humlum 2019; Koch et al. 2019; Dixen et al. 2019; Cheng et al. 2019).[4] 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 2019).[5] 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 (Acemoglu et al. 2020, Humlum 2019, Koch et al. 2019).

Our study delves into this question by examining the early phase of robot adoption in the nursing home industry in Japan, where the government has promoted adoption of robots as a strategy to address the shortage of care workers in the face of the decline in working-age population. Thus, Japan’s long-term care system is in many ways the ideal setting to study how robotic technologies will interact with aging societies, especially when facing a declining overall population. In fact, it is projected that as many as 18 out of 36 OECD countries will face declining populations by 2055 (United Nations 2017). As many more countries face aging populations, Japan’s case will help shed light on how demographics interact with the debate surrounding new automation technologies.

[2] Studied settings include the US (Acemoglu and Restrepo 2020), Canada (Dixen et al. 2019), China (Cheng et al. 2019), Japan (Adachi et al. 2020), South Korea (Lee and Lee 2020), France (Acemoglu et al. 2020), Spain (Koch et al. 2019), Denmark (Humlum 2019), and Germany (Dauth et al. 2017), among others.

[3] Much of the discussion up to now has appeared in industry reports or health care journals with a focus on the technology itself rather than the consequences for labor (Qureshi and Syed 2014; Huston 2013).

[4] 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).

[5] 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.

We study this issue using survey data from 2017 for about 860 nursing homes in Japan. The data contain various staffing information, such as the number of nurses and care workers, their wages, and turnovers, along with other nursing home characteristics, including whether the nursing home adopts robots. In Japan, national government has actively promoted the development and use of robots in long-term care and local governments provide subsidies to adopt robots in nursing homes. Our empirical identification strategy utilizes this variation in robot subsidies across prefectures.[6] OLS may be problematic because staffing and adoption of robots are correlated with other characteristics of the nursing home, its other technology, and management. Because the decision to subsidize robots for long-term care (LTC) may be correlated with local labor market conditions, we control for various factors that may affect the demand for and supply of care workers in the local economy.

In the setting of long-term care for the elderly, demographic change may have already spurred significant development of robotics technology (Acemoglu and Restrepo 2018) and the belief that robots can substitute for workers, bolstering the declining supply of care workers as the demand for care (i.e., the number of older adults requiring long-term care) 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 compassion, empathetic communication, and emotional connection (MGI 2017, Jackson *New York Times* December 14, 2019). These areas embody the continuing or new tasks in which labor has a comparative advantage. Furthermore, robots may reduce turnover and side effects such as back pain, while potentially increasing the quality of care from reduced falls and injury. Ultimately the effect of robots on staffing is an empirical question, since conceptually, the impact could be either to complement or substitute for various tasks of current care workers and nurses.

We find that robot adoption increases the number of care workers and nurses. Interestingly, these effects are concentrated on non-regular employees and have no effect on regular employees. Non-regular workers are on more flexible employment contracts but with fewer benefits. We also find that robot adoption reduces the monthly wages of regular nurses. This may be due to the reduction of care burden at night, including night shift hours, afforded by monitoring robots, the kind of robot most frequently adopted by nursing homes. Finally, robot adoption reduces the likelihood of nursing homes reporting difficulty in staff retention,

[6] There are 47 prefectures in Japan.

which is consistent with the intent of subsidizing robot adoption, i.e., reducing the burden of care workers. Taken together, our findings indicate that robot adoption does not reduce jobs, but promotes more flexible work, either by increasing non-regular employees or potentially encouraging part-time work. Our findings are among the first to examine to what extent robots complement or substitute workers in the service sector using establishment-level data, uncovering hints of which specific tasks and worker types are most likely to have been affected since 2017 and going forward in tight labor markets.

In addition to the literature already mentioned, this study relates to the literature on automation and its implications for labor share (Autor and Salomons 2018; Acemoglu and Restrepo 2019), as well as the emerging literature that focuses on artificial intelligence and jobs (Felten et al. 2018; Brynjolfsson et al. 2018; Webb 2020). Also, our study contributes to the literature on nursing homes and the economics of automation for labor providing long-term care services. Our empirical work brings Japanese data to expand and test hypotheses and trends documented in the US and Europe regarding nursing home staffing (Hackmann 2019, Chen et al. 2020), facility characteristics (e.g. Banaszak-Holl et al. 2018) and quality of care (Castle 2008; Zhang and Grabowski 2004), as well as the parallel literature on skilled nursing facilities (e.g. Rahman, Norton and Grabowski 2016).

In the remainder of this paper, we first describe the setting, our data, and empirical strategy. Our empirical results first document the correlates of robot adoption, and then utilize our IV strategy to examine the effects of robot adoption on staffing, wages, turnover, and wage share. A short discussion concludes.

2. Robot Adoption and Long-Term Care in Japan

2.1. Japan’s demographic challenges and shortage of care workers

Because of rapid aging, the demand for long-term care is expected to dramatically increase in Japan. Figure 1 illustrates the growing demand for long-term care, in several related panels. The two maps in panels A and B show a geographic snapshot of the proportion aged 70 and older, and the share of nursing home residents with the most severe functional limitations (care-required levels 4 and 5). Panel C graphs the increase in population in Japan aged 75 and older, showing the significant projected increase in the coming decades in the proportion aged 85 and older, sometimes called the “oldest old.” The expansion of this population signifies the increasing demand for long-term care services in

Japan, including assistance with basic activities of daily living such as eating, toileting, and bathing.

At the same time, the supply of care workers may not grow to meet the demand (Figure 2 Panel A), as official projections indicate a shortfall of 380,000 care workers by 2025 (MHLW 2017), although the shortfall depends to some extent on local labor markets and national policies regarding accepting more immigrant labor. The growing demand and limited supply have translated into a tight labor market for care workers, with the ratio of job offers to applicants about twice the average in Japan (Figure 2 Panel B). The shortage of care workers—those who provide direct contact care to older or disabled clients through assistance with tasks of daily living like toileting and bathing—has been blamed on several factors, including that care workers are not well compensated and often experience physical repercussions such as lower back pain.[7] In particular, care worker wages barely exceed the minimum wage. As Appendix Table 1 indicates, the average hourly pay for care workers was 965 Yen in 2017, compared to the average minimum wage of 902 Yen.

2.2 Subsidizing care robots

For many years, Japan has been a leader in terms of robot production and utilization, and Japan is now seeking to use robots to cope with its demographic challenges. The government has implemented several programs to promote robots in long-term care for older adults. On the supply side, the government has subsidized development of nursing care (or "*kaigo")* robots (i.e., robots used in long-term care, mostly for frail elderly) as part of Japan's growth strategy. The latest version of Japan's "Robot Strategy," laid out by a body within the cabinet of the Japanese government, articulates several specific goals: increasing the share of people who want to use robots for providing care from the currently estimated 60% to 80%; lowering the risk to care workers of suffering back pain (ultimately to zero) by using robots for helping with transfers; and enabling faster pre-market review for new medical devices.[8] 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 eight task areas such as transfer aid and communication for which they subsidize development of long-term

[7] 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.

[8] See complete report at http://www.meti.go.jp/english/press/2015/pdf/0123_01b.pdf.

care 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.)

On the demand side, starting in 2015, the central government set aside funds for each prefectural government to utilize to improve its local long-term care services. Subsidies for purchasing nursing care robots were part of a menu of items for which funds could be used. Some prefecture-level governments started subsidizing the cost of adopting long-term care robots in 2015. The subsidies typically cover 50% of the cost, up to 100,000 yen (approximately US$1,000) per robot. Prefecture governments usually specify a planned number of robots they will subsidize in a given 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. As we discuss later in Section 3.2, we use this cross-prefectural variation in the planned number of robots subsidized as an instrument for robot adoption. In April 2016, additional prefectures introduced the adoption subsidy. 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 long-term care facilities, totaling 5.3 billion yen (approximately US$53 million), with up to 3 million yen (US$30,000) per establishment.

2.3 Robots in nursing homes

Appendix A illustrates the categories of long-term care robots we discuss in this paper, including the categorization of nursing care robots developed by the Japanese government and used in their survey of long-term care 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,[9] 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 these into three main categories: transfer aid robots, mobility robots, and communication and monitoring robots.

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%.[10] 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.

2.4 Long-term care in Japan

Japan implemented universal long-term care insurance starting in year 2000. The insurance covers eligible elderly above age 65, evaluated for care need levels, covering payments to care providers for day-care services, in-home services, and residential nursing homes for long-term custodial care. (It does not pay family members for care at home.) The levels of care required or "*Kaigo* Neediness Index" are described in the appendix; they vary

[9] http://www.techno-aids.or.jp/robot/file29/jirei2017.pdf
[10] https://kaigorobot-online.com/contents/52

from level 1 ("mostly able to eat and use the bathroom independently" but "requires some form of help in taking care of the surroundings") 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"). The government regulates public long-term care service prices, which are uniform across nursing homes.

3. Data and Empirical Strategy

3.1 Facility-level data

We analyze facility-level data from the annual Fact-Finding Survey on Long-term Care Work collected by the Care Work Foundation in Japan. [11] More than 8,000 long-term care facilities are surveyed each year, with survey questions about adoption of robots included since 2016. [12] The survey is fielded to a random sample of facilities that provide a variety of in-home, day-care, and custodial long-term care services, with a response rate of about 50%.

In this study, we focus on approximately 860 nursing homes that responded to the survey. There are two types of nursing homes. The first is the "custodial type" or "*tokuyo*" in Japanese, where users reside in the facility and receive long-term custodial care—such as assistance with eating, toileting, and bathing—usually for the remainder of their lives. The other is the "skilled nursing type" or "*roken*" in Japanese, providing intensive, medium-term (3-6 months) rehabilitation services; many of the residents come directly after being discharged from the hospital. These facilities resemble skilled nursing facilities in the US.

There are also two types of caregivers entrusted with hands-on care for the clients of these facilities: care workers and nurses. The former assist residents with activities of daily living; they are subject to three different levels of licenses but nevertheless relatively low-skilled and low paid, as noted previously. Nurses perform a variety of clinical, rehabilitative and caregiving tasks, and are subject to more restrictive licensing entitling them to provide nursing services in medical facilities such as hospitals and clinics. Both are overwhelmingly staffed by women. Regulations in Japan require both types of nursing homes to maintain a 3:1 ratio of residents per caregiver, i.e., care workers plus nurses must total at least one for every 3 residents. A part-time medical doctor is sufficient for custodial nursing homes. For

[11] 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.
[12] We attempted to conduct the same analysis for 2016 but the instrumental variable was too weak to do so, probably because many fewer prefectures provided robot adoption subsidies in that year.

the skilled nursing facilities, there is an additional nurse staffing requirement of 7:1 (i.e., one nurse per seven residents), and the facility must have a full-time medical doctor on staff.

To provide suggestive evidence about the representativeness of the survey (given potential selection among respondents), we compare to the universe of such facilities for the type most likely to adopt robots (regular size custodial care residential facilities).[13] As shown in the multiple panels of Appendix Figure 2, 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.[14] Overall the survey appears reasonably representative.

The survey provides information not only about each facility, but also a sample of worker-level variables including wages. The survey asks nursing homes to report the wage of up to 20 employees, selected to be representative of average employees in that facility, such as those with long or short tenure at the facility. The 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). We utilize these data to examine the relationship between robot adoption and wages, controlling for other worker characteristics. While the sample of care workers is ample (6,360 regular, monthly-wage care workers and 1,674 non-regular, hourly wage care workers), that of nurses is smaller (i.e., 1,251 regular nurses with monthly wages), and results for non-regular, hourly-paid nurses should be interpreted with caution, given the limited number of nurses of that type (196) included in the survey.

The Survey also includes questions about human resource management, providing useful information about management practices or even proxies for management quality. These include answers to 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

[13] 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.

[14] 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 is supposed to contain information only for a specific type of long-term care service.

working conditions such as by reducing overtime work or making it easier to take paid leave? To increase retention do you increase wages? We include these variables to capture differences in management practices.

3.2 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 for purchase of robots supporting long-term care for frail elderly residents. Based on the documents we gathered, it seems clear that since 2015 more and more prefectures began to subsidize nursing homes' acquisition prices for long-term care 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, set aside to improve long-term care services in each prefecture.[15] Prefectures use the funds to subsidize nursing homes to purchase nursing care robots. We reviewed each prefecture's reports starting in FY2015 to extract information on how they subsidize nursing homes for robot purchases.[16] We then directly contacted each prefecture to confirm these numbers.

From this unique dataset, we utilize two primary measures: the 2017 planned number of 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" serves as our main instrumental variable for robot adoption at the facility level. Figure 3 illustrates the magnitude and geographic variation in these measures of planned subsidies for nursing care robots. Panel A maps the number of planned robots subsidized in each prefecture, and panel B maps the planned number of robots subsidized per nursing home (or "planned robot exposure").

[15] Documentation about use of these funds, called "*chiiki iryo kaigo sougo kakuho kikin*," is available through the MHLW at https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/0000060713.html.

[16] 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. 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.

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

We first document the association of robot adoption with various characteristics of nursing homes. Then to identify the causal impact of robots on staffing, we use the prefecture subsidies an instrumental variable for the adoption of robots in nursing homes.

3.3 Description of robot adoption landscape

We start by describing what types of robots have been adopted for what kinds of services within residential facilities in Japan, as reported by respondents to the Survey in Japan. In 2016, 17.6% of nursing homes reported using any type of robot, rising to 26% among the 857 nursing homes surveyed in 2017 (the focus of our study). 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 of robots used by facilities 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. The appendix provides illustrations of each type of robot and how they are used in caregiving.

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 4 shows a bin scatterplot with 20 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 covered in the survey, with facilities dichotomized into adopters and non-adopters (of any robot), and the final columns show the total. The average nursing home in our survey employs 42 care workers, 8 nurses, and 80 total staff, the majority (66%) of whom are regular (generally full-time, monthly wage) employees. Facilities have been in operation on average for a little over 17 years. 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 (32.1%) 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 long-term care insurance are not-for-profit organizations.[17]

Facilities that had acquired at least one robot were slightly larger with more staff (Table 2). Robot-adopting nursing homes had more care workers (mean 47.7 vs. 40.4) and more nurses (8.7 vs. 7.7) compared to their counterparts without robots, although the differences in staff per resident are not significant. Robot-adopters have a slightly lower separation rate of care workers, a higher percentage reporting that they currently employ immigrant labor (21% compared to 14% among non-adopting nursing homes), and fully 10 percentage point higher reported intention to hire immigrant labor in the future (41% vs. 30%).

Robot-adopting homes also 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 also more likely to own almost all the other forms of assistive technologies (e.g. adjustable beds, lifts for movement, and so on). However, robot adoption does not significantly differ between custodial versus skilled nursing facilities or by ownership type.

Next, we show summary statistics for the aforementioned survey questions about human resource management. Robot-adopters are 10 percentage points more likely to have a human resource manager (68% vs 58%) and are more likely to report that they make effort to improve wages for retention of employees (59% vs. 45% among non-adopters). Robot-adopters are also more likely to offer training to new employees. In terms of prefecture

[17] 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.

characteristics, robot-adopters tend to be in more populous, aged prefectures with higher unemployment rates and minimum wages.

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. As alluded to, 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. Overall, residents per care worker plus nurse in the sampled nursing homes fall well within the required staffing ratios: custodial nursing homes average 1.3 residents per care worker and 8.7 residents per nurse; skilled nursing homes average 2.1 residents per care worker and 6.1 residents per nurse.

3.4. Estimation specification

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

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

where $Robots_{jk}$ is an indicator variable for whether nursing home *j* in prefecture *k* has adopted any robots for long-term care. 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 corporation, local government, and other). Also included in Z_j are perceptions of managers of facilities regarding the shortage of care workers and nurses, and difficulty of hiring high quality care workers. We created these variables by averaging across nursing homes in the same locality, but excluding nursing home *j* (we label these leave-one-out variables as "labor shortage perception controls" in the tables). 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, 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 μ_{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 and wages, where S_k is the excluded instrument.

Next to identify the causal effect of robot adoption on staffing, we estimate regressions of the following form:

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

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 relationship between robot adoption and wages:

$$Y_{ijk} = \alpha_0 + \alpha_1 Robots_{jk} + \alpha_2 W_i + \alpha_3 Z_j + \alpha_4 P_k + \mu_{ijk}\ , \quad (2')$$

where Y_{ijk} represents the wage of worker *i* at nursing home *j* in prefecture *k*. W_i captures individual characteristics including gender, age, age squared, qualifications (e.g., whether the worker has a certification), tenure, and tenure squared. We look separately at wages of care workers, nurses, and managers, as well as the difference between regular and non-regular care workers and nurses.

Of course, there may be numerous 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 and wages. 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 mitigate this concern, we control for various demand and supply side factors that would affect the tightness of the labor market, including elderly population aged 70 and older, per capita income, minimum wage, unemployment rate, and the ratio of job openings to applicants. 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.

4. Empirical Results

4.1 Robot adoption

What are the primary predictors of robot adoption for long-term care? Table 3 shows the results for our estimation of equation (1). All regressions also control for years of operation; location (metropolis, urban, rural); corporation type (social welfare council, social welfare organization, medical corporation, local government, and other); and an indicator for skilled nursing homes. Standard errors clustered by prefecture are in parentheses.

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. 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 wheel chair lifts and wheel chair 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 an HR manager and "seeking to improve wages for retention" 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). Appendix Table 4 presents the coefficient estimates on the additional variables included in columns 5 to 7. Finally, we see in the last two columns 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). Planned number of robots per nursing home is our instrument for identifying causal effects of robot adoption on staffing and wages. We use the column 9 specification for our IV regression.

4.2 OLS results

We next turn to the relationship between robot adoption and nursing home staffing. Table 4 shows 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 first three columns show the different kinds of staff: care workers, nurses, and total number of workers (whether providing 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.

We next turn to wages (columns 4 to 8). Since worker characteristics are a powerful determinant of wages, in these regressions we control for various worker attributes as specified in Equation (2'). We find that robot-adopting nursing homes do not seem to have a different wage structure than their non-adopting counterparts, though the negative estimates hint that they may be offering lower wages.[18]

4.3 IV results

Table 5 reports our staffing and wage results using planned number of robots subsidized per nursing home in 2017 as the IV to identify the causal effect of robot adoption. The impact of robots on staffing is positive and significant for both care workers and nurses. The estimate suggests that robot adoption leads to about 28% more care workers and 39% more nurses. Total employees increase by about 26%. 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 does not displace workers but may complement investments in higher quality care by increasing care workers and nurses with more flexible labor contracts.

After using the instrumental variable, the coefficient estimates on robot adoption become significantly positive. This may happen, for example, if an unobserved negative

[18] We also examined the relation between staffing and robot adoption by type (Appendix Table 5 Panel A) and the year in which the facility acquired the robot (Panel B). 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 (Panel B), 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% higher numbers of staff, with the association only significant for regular employees. We see in Appendix Table 6 negative association with wages of non-regular nurses, especially for monitoring and communication robots, and with robots first adopted before 2017. However, robot adoption is not correlated with nurses' monthly wages -- which are more common than hourly wages, and virtually the only form of payment for regular employees.

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 the OLS estimate on robot adoption would be negatively biased; the IV regression that removes the confounding effect would result in a more positive coefficient estimate.

Robot adoption reduces monthly wages of nurses, especially of regular nurses, whose wages decrease by about 22%. The IV estimate on non-regular nurse (hourly) wages are unreliable due to the small sample and low first stage F-statistic. The estimates for care-workers are also negative but the magnitudes are smaller (2.8 to 6%) and not statistically significant. As we noted before, care-worker wages are only slightly greater than the minimum wage, and this wage floor limits how much care worker wages can decrease. On the other hand, robot adoption seems to increase manager wages by about 18%, though the estimate is not significant. The IV estimates indicate that the OLS estimates in the wage regressions were positively biased. This could be due to unobserved local labor market conditions, such as the difficulty of hiring caregivers, being positively correlated with wages and robot adoption.

The reduction in nurse monthly wages may reflect reduction in caregiver burden during night shifts, since the most frequently adopted kind of robot, monitoring robots, are specifically designed to substitute for tasks such as frequent night-time rounds to monitor residents' well-being, which are provided by regular employees. According to a government survey on the effectiveness of care robots,[19] 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.

In Table 6 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. Panel A examines regular employees, and Panel B examines 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

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

suggests that nursing homes use the subsidy to primarily install monitoring or aid robots. The estimates we find in Table 5 are most similar with the estimates from monitoring robots, which is the category of robot most commonly adopted by nursing homes. The increase in non-regular staffing and reduction in regular nurse wages we find in Table 5 is largely driven by monitoring robots and aid robots. Indeed, the wage reduction from robot adoption may likely be attributable to monitoring and aid robots, which assist nurses and care workers, especially during night shifts. The estimate for regular care worker is smaller in magnitude, which may be due to care worker wages being low and the downward limit set by the minimum wage.

The reduction in nurse monthly wages may also be due to more nurses taking up part-time hours. The MHLW and the Japanese Nursing Association have been encouraging part-time regular workers as a way for workers to retain their regular status while working shorter hours to increase flexibility in employment patterns.[20]

Table 7 shows results for wage share and revenue growth of nursing homes. The IV estimate indicates that robot adoption significantly reduces the wage share by 7.7% points, which is consistent with the decrease in nurse wages and the increased investment in capital, i.e., robots. Revenue growth is not significantly impacted by robot adoption. Table 8 column 1 examines whether robot adoption affects retention of workers. The outcome is a dummy variable indicating whether retention of workers at the nursing home is low and is considered a problem. Given the physically demanding nature of the care giving and low pay, retention can be a challenge in many nursing homes. 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 (Appendix Table 7).

For Japan, the use of foreign employees is especially of interest, as policies have long discouraged much immigration but have just recently begun to be relaxed, in part to relieve the forecasted shortfall of LTC workers. In Table 8 columns 2 and 3, we show OLS and 2SLS results regarding nursing home hiring of foreign workers in 2017. Consistent with

[20] According to the Labor Force Survey of 2017 by the Statistics Bureau of Japan, the possibility to balance demands of at-home production (i.e., housework, childcare, elderly care) with supplemental household income during flexible work hours was the main reason why female non-regular workers reported desire to remain in their current status. In the Long-term Care Work survey that we use, more than 60% of non-regular nurses and care workers in custodial care nursing homes did not want to become regular workers.

what was already evident from the descriptive statistics, nursing homes that adopt robots (especially aid robots) are more likely to have hired foreign workers, but this association is not causal (column 2). A similar pattern applies to reported plans to hire immigrant labor in the future: while future hiring of foreign workers has a significant positive association with robot adoption, the 2SLS estimate is indistinguishable from zero.

In Appendix Table 8, 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. Since our robot adoption variable measures whether the nursing home has any robots in 2017, the robot subsidy in the previous year would likely be a relevant instrument as well. The first-stage F-statistics are somewhat smaller than the estimates we get when we use the 2017 subsidy variables, though still considerably greater than 10. Overall, we find that the results are qualitatively and quantitatively similar to the results when using the 2017 subsidy variable. We also examine our key results on staffing and wages while limiting our sample to custodial nursing homes only and find that results are not sensitive to the inclusion of skilled nursing facilities (Appendix Table 9).

5. Conclusion

To date, there has been little firm-level evidence on the labor market impact of robotics in the service sector, or across countries with different demographic profiles. Yet most middle- and high-income economies have large or dominant service sectors, so that establishment-level evidence about robot use in service delivery may be even more important than industrial robot diffusion for understanding current and future economic impacts. Moreover, demography matters. The same new wave of technologies that inspires fear 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 any 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 long-term care workers.

Examining establishment-level 2017 micro-data from Japan from the Fact-Finding Survey on Long-term Care Work, we find that robot adoption increases, rather than decreases, the number of care workers and nurses, by primarily adding non-regular jobs. Employment contracts for non-regular workers often are temporary and flexible, offering fewer benefits than those enjoyed by regular employees. We also find that robot adoption reduces the monthly wages of regular nurses. We surmise that this may be attributable to the reduction of care burden during night shifts, since monitoring robots may reduce frequent night-time rounds to monitor residents' well-being and night shift hours. Additionally, adoption of monitoring robots might have promoted part-time hours by regular nurses. The Japan Nursing Association has been encouraging part-time regular work contracts to reduce stress on nurses and promote work-life balance. Finally, consistent with reduced burden of care, robot adoption reduces the likelihood of nursing homes reporting difficulty in staff retention. Taken together, our finding indicates that robot adoption does not reduce jobs, but promotes more flexible work, either by increasing the tasks performed by non-regular employees or potentially encouraging part-time work.

The effects of robots that we find may be generalizable to some extent beyond the specific context of nursing homes in Japan, since the working and employment conditions—strenuous work, low pay, and high turn-over—are common aspects of many service sectors in other countries as well. Moreover, aging and declining populations is inevitable for a large number of OECD countries, and their labor markets may soon face similar challenges as Japan does.

Over time, staffing may need to be re-engineered to reflect new groupings of tasks. At this early stage, robots may be augmenting care workers on specific tasks and not having negative staffing effects yet, as organizations experiment with how best to incorporate robotics into the routines of a nursing home. Eventually automation may lead to more meaningful work and less stress, monotony, and error, although whether regular or non-regular care workers and nurses will enjoy these benefits is less clear.[21]

Our findings are broadly consistent with predictions that the jobs that complement robotics in the service sector are lower-paying ones (e.g. MGI 2017), since we find the employment increase was for nonregular care workers and nurses, those who receive fewer employer-provided benefits. On the other hand, we cannot rule out that part of the effect or even the primary effect involved upskilling, as for example would occur if monitoring robots replaced nurse tasks during long and tedious night shifts, allowing them to work fewer hours while focusing on higher-skill components of their jobs. It is not clear if the reduction in

[21] Robot adoption without reduction in staffing may also have unmeasured benefits in specific circumstances, such as complementing telemedicine and social distancing to protect frail elderly populations during a pandemic like COVID-19 or in future seasonal influenza epidemics, supplementing caregiving tasks when care workers in nursing homes and other post-acute care settings may be stressed. Although this aspect of robot adoption has not yet been studied, we plan to do so in our follow-up research. For comparative views from the US during the COVID-19 pandemic, see for example Grabowski and Joynt Maddox (2020).

effective work hours from fewer or less onerous night shifts more than outweighed the reduction in monthly wages. Certainly, care workers and nurses in robot-adopting nursing homes would be learning the new tasks associated with incorporating relatively cutting-edge technologies into everyday caregiving tasks, and are well-placed to give feedback to manufacturers and management about robot design and usage.

This study provides a foundation for continuing to monitor the effects of robot adoption in long-term care services in Japan and elsewhere in the world. Whether our results represent only an early period of diffusion, or mask impacts that complement or augment some types of labor while substituting for others, merits continued research. To fully understand the impact of automation on work, we need to follow the evolution of labor markets and automation over longer periods of time. Japan may be a harbinger for aging populations and economies around the world. However, with only one or two cross-sections of data with limited and recent overall robot adoption, we may see few definitive impacts and not yet be able to discern patterns that evolve or cumulate over time. Moreover, one of the primary impacts of robots, on quality of care, is largely unmeasured in the survey we used. Future analysis that focuses on the impact of automation on quality of care in nursing homes would provide a fuller picture of how automation effects jobs and productivity in the service sector.

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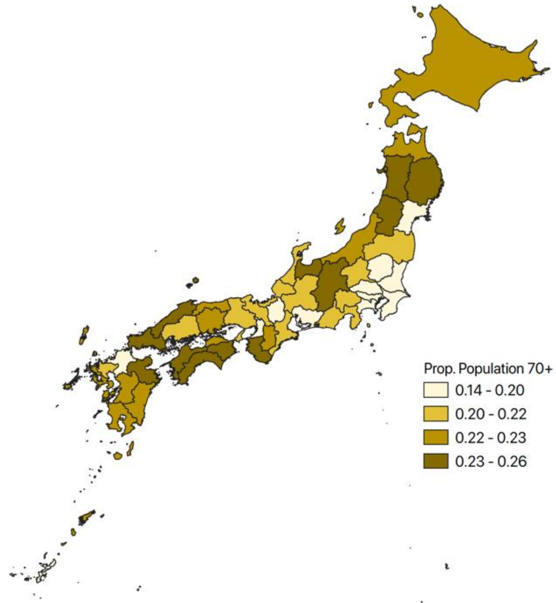
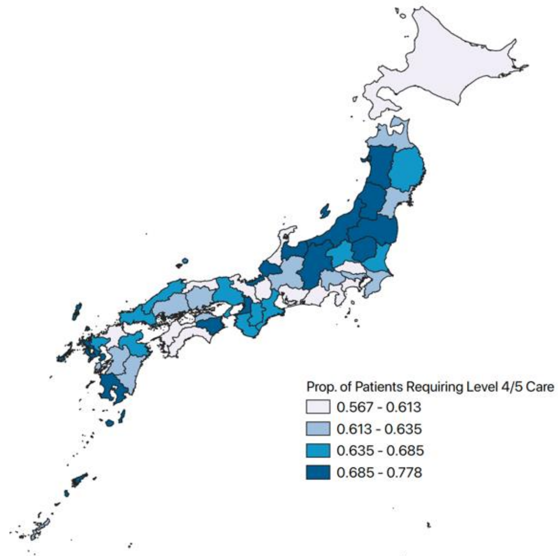
Figure 1. Demand for long-term care (LTC) in Japan

A. Proportion of population ages 70+

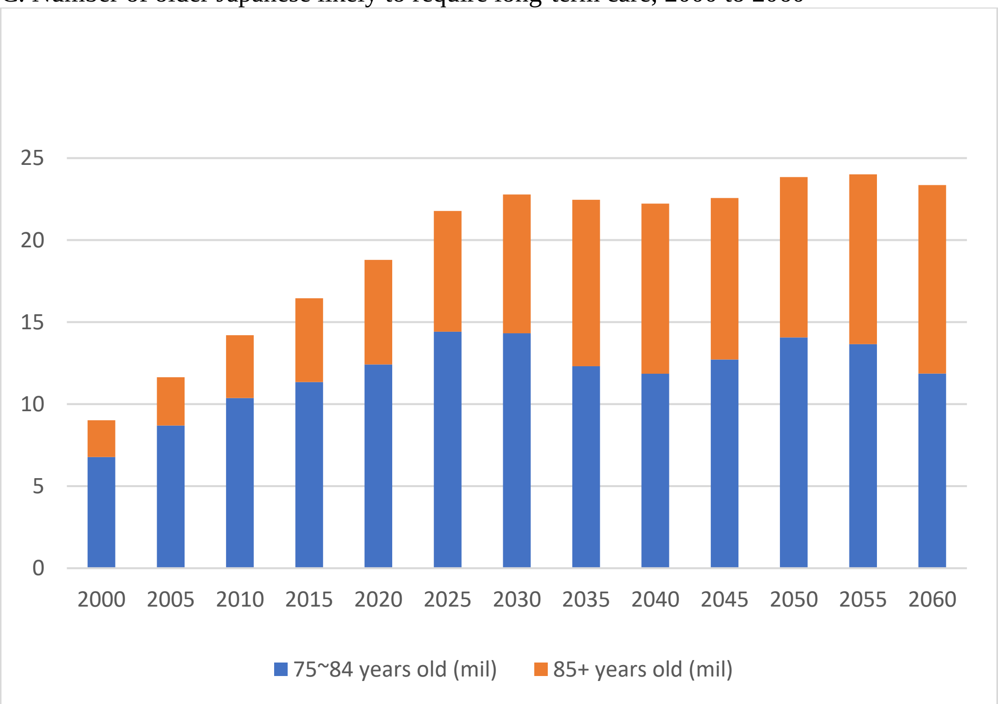


B.Proportion of nursing homes residents with substantial functional limitations (level 4/5 care)



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

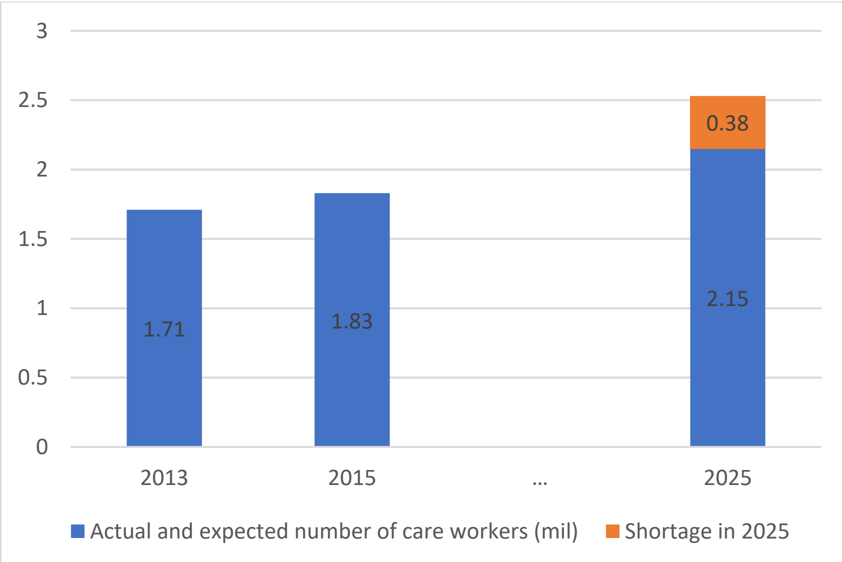
C. Number of older Japanese likely to require long-term care, 2000 to 2060



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

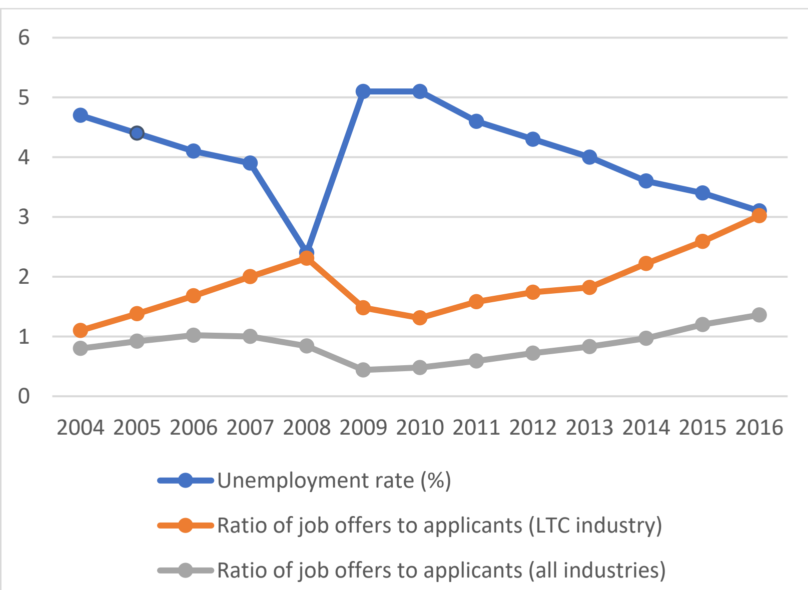
Figure 2. Supply of LTC workers and labor markets in Japan

Panel A: Actual vs. expected number of care workers



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

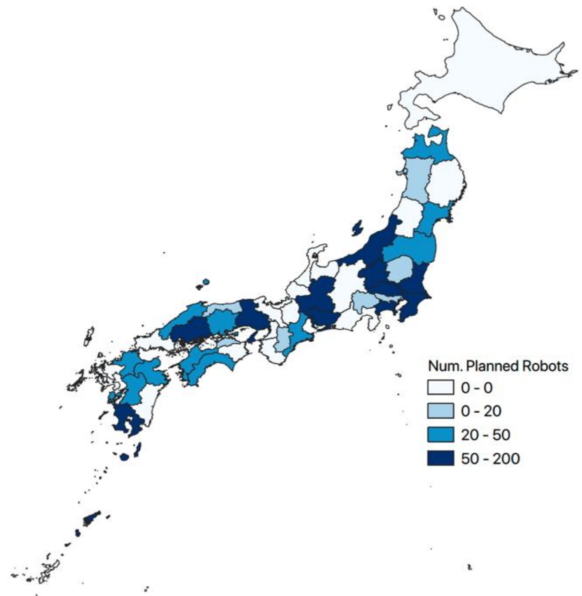
Panel B: Ratio of job offers to applicants for the LTC industry in comparison

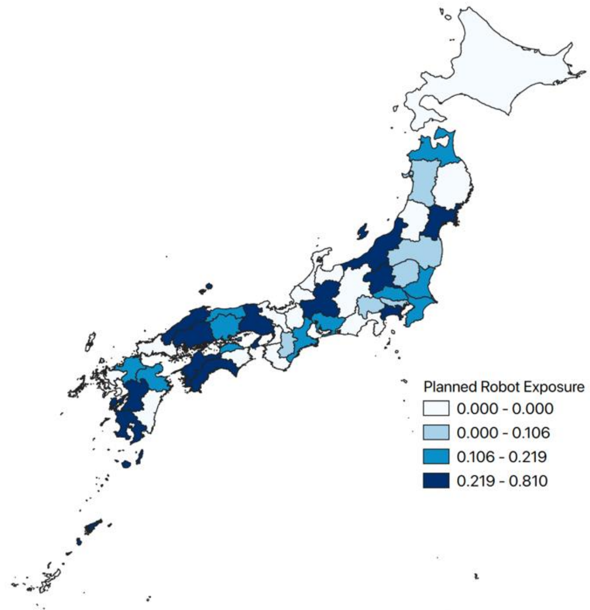


Data source: Employment Security Statistics (MHLW), Labor Force Survey (MHLW)

Figure 3. Subsidies for nursing care robots

Panel A: Number of planned robots (2017) Panel B: Planned robot exposure (2017)

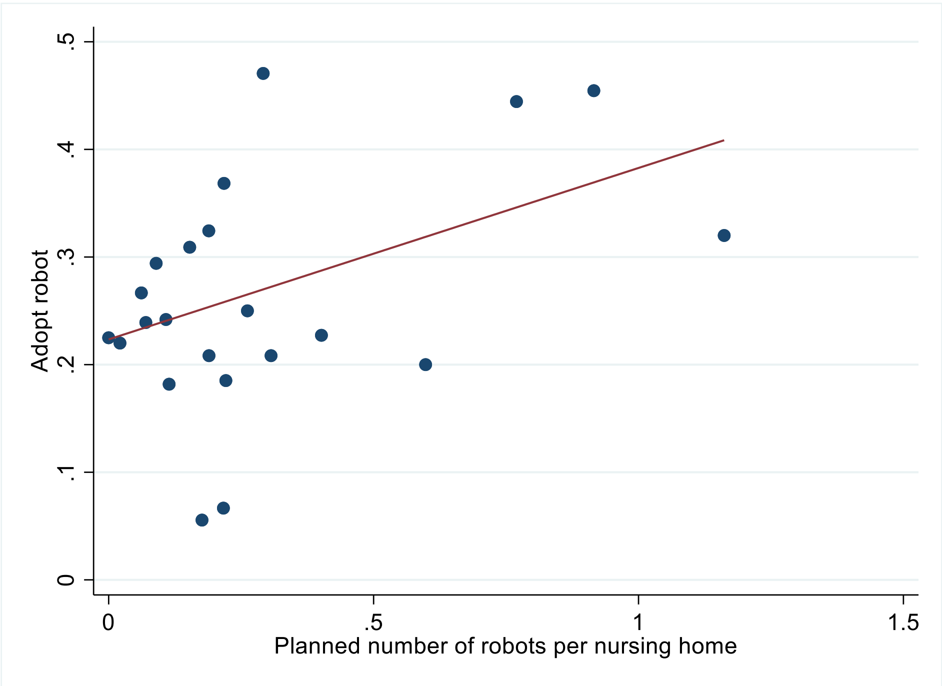




Source: Ministry of Health, Labor and Welfare, Japan. Various years. Prefectural report on funds set aside to improve health care and long-term care service in each prefecture ("*chiiki iryo kaigo sougo kakuho kikin*"). https://www.mhlw.go.jp/stf/seisakunitsuite/bunya/0000060713.html.

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

Figure 4: Subsidies for nursing care robots predict robot adoption, 2017



Source: Binscatter plot, using 30 bits, 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	Obs
Adopt robots	0.260	0.439	0	1	857
Adopt aid robots	0.077	0.267	0	1	857
Transfer aid: wearable	0.047	0.211	0	1	857
Transfer aid: non-wearable	0.033	0.178	0	1	857
Adopt mobility robots	0.053	0.223	0	1	857
Mobility aid: outdoor	0.005	0.068	0	1	857
Mobility aid: indoor	0.008	0.090	0	1	857
Excretion support	0.005	0.068	0	1	857
Bathing support	0.029	0.168	0	1	857
Adopt communication robots	0.174	0.379	0	1	857
Monitoring facility	0.149	0.357	0	1	857
Communication robots	0.028	0.165	0	1	857
Robot subsidy	0.719	0.450	0	1	857
Planned number of robots subsidized per nursing home	0.210	0.269	0	1.162	857

Table 2. Descriptive statistics

	Robot non-adopter		Robot adopter		Difference of Means		Total	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Number of care workers	40.350	0.753	47.700	1.498	-7.350***	1.556	42.242	0.687
Number of nurses	7.695	0.199	8.683	0.295	-0.988***	0.380	7.943	0.167
Number of total staff	77.635	2.717	87.429	2.838	-9.794**	4.925	80.169	2.155
Number of care workers - regular employees	28.162	0.569	33.004	1.060	-4.842***	1.153	29.404	0.508
Number of nurses - regular employees	5.110	0.163	5.604	0.243	-0.494	0.312	5.233	0.136
Number of total staff - regular employees	51.928	2.037	56.754	1.814	-4.826	3.634	53.172	1.588
Care worker log monthly wage	12.496	0.003	12.498	0.006	-0.002	0.006	12.497	0.003
Nurse log monthly wage	12.708	0.008	12.724	0.011	-0.016	0.015	12.712	0.006
Manager log monthly wage	13.230	0.020	13.272	0.027	-0.041	0.038	13.241	0.016
Separation rate of care workers	0.156	0.009	0.143	0.007	0.013	0.015	0.152	0.007
Hiring rate of care workers	0.161	0.005	0.162	0.010	-0.001	0.011	0.161	0.005
Turnover rate of care workers	0.316	0.012	0.305	0.016	0.012	0.023	0.313	0.010
Report retention as a problem	0.327	0.018	0.307	0.030	0.020	0.035	0.321	0.015
Hire foreign workers	0.143	0.013	0.208	0.026	-0.065**	0.027	0.160	0.012
Plan to hire foreign workers	0.297	0.017	0.405	0.032	-0.108***	0.035	0.325	0.015
Years of operation	17.709	0.387	17.715	0.578	-0.005	0.742	17.708	0.324
Number of residents requiring care level 1, 2, or 3	25.460	0.786	25.446	1.246	0.014	1.526	25.420	0.665
Number of residents requiring care level 4	22.287	0.405	24.633	0.813	-2.347***	0.839	22.896	0.368
Number of residents requiring care level 5	18.788	0.412	20.921	0.681	-2.133***	0.808	19.334	0.354
Care workers per resident	0.684	0.025	0.720	0.022	-0.035	0.045	0.694	0.019
Nurses per resident	0.124	0.003	0.130	0.004	-0.006	0.006	0.125	0.003
Skilled nursing home	0.211	0.015	0.183	0.025	0.027	0.030	0.203	0.013
Social welfare council	0.021	0.005	0.017	0.008	0.005	0.011	0.020	0.005
Social welfare organization	0.784	0.016	0.842	0.024	-0.058*	0.030	0.799	0.013
Medical corporation	0.150	0.014	0.121	0.021	0.030	0.026	0.143	0.011
Local government	0.029	0.006	0.008	0.006	0.020*	0.011	0.023	0.005
Wheel chair lifts	0.722	0.017	0.825	0.025	-0.103***	0.032	0.748	0.014
Adjustable beds	0.918	0.010	0.954	0.014	-0.036*	0.019	0.928	0.008
Seat lifting wheel chair	0.090	0.011	0.108	0.020	-0.018	0.022	0.095	0.010
Special bathtub	0.799	0.015	0.863	0.022	-0.063**	0.029	0.816	0.013
Stretcher	0.867	0.013	0.938	0.016	-0.071***	0.024	0.885	0.010
Wheel chair for showers	0.649	0.018	0.742	0.028	-0.093***	0.035	0.673	0.015
Wheel chair scale	0.900	0.011	0.983	0.008	-0.084***	0.020	0.921	0.009
Has employment regulation for non-regular workers	0.926	0.010	0.908	0.019	0.017	0.020	0.921	0.009
Has a HR manager	0.580	0.019	0.675	0.030	-0.095***	0.036	0.604	0.016
Has a wage table	0.911	0.011	0.938	0.016	-0.026	0.021	0.918	0.009
Improve working conditions for retention	0.576	0.019	0.579	0.032	-0.003	0.037	0.577	0.016
Improve wages for retention	0.451	0.019	0.592	0.032	-0.140***	0.037	0.487	0.016
Additional Provider Payment	0.971	0.006	0.988	0.007	-0.016	0.012	0.975	0.005
Log(per capita income)	7.986	0.006	7.985	0.010	0.001	0.011	7.986	0.005
Unemployment rate	2.550	0.020	2.665	0.030	-0.114***	0.038	2.580	0.017
Log(total population)	14.773	0.031	14.923	0.053	-0.150**	0.062	14.811	0.027
Log(population 70 or older)	13.203	0.028	13.343	0.048	-0.140**	0.056	13.239	0.025
Minimum wage	805.529	2.353	814.038	4.342	-8.509*	4.753	807.706	2.076
Log(number of nursing homes)	5.558	0.022	5.664	0.037	-0.106**	0.044	5.585	0.019
Jobs hired per opening	0.720	0.004	0.738	0.008	-0.018**	0.009	0.724	0.004

Nursing home job openings per applicant	3.566	0.043	3.656	0.073	-0.089	0.086	3.589	0.037
Occupancy rate of nursing homes	0.940	0.0004	0.937	0.001	0.002***	0.001	0.939	0.0004
Log (Number of people certified for care level 3 in the prefecture)	9.830	0.026	9.966	0.045	-0.136***	0.052	9.865	0.023
Log (Number of people certified for care level 4 in the prefecture)	9.755	0.026	9.896	0.044	-0.141***	0.051	9.791	0.023
Log (Number of people certified for care level 5 in the prefecture)	9.474	0.027	9.624	0.045	-0.149***	0.053	9.513	0.023
Prefecture subsidies for securing workers	1.254	0.044	1.175	0.072	0.792	0.086	1.234	0.038
Prefecture subsidies for improving facilities	10.221	0.271	11.535	0.454	-1.315**	0.533	10.557	0.233
Log (Estimated population in 2040)	14.602	0.033	14.758	0.056	-0.156**	0.066	14.642	0.029
Log (Estimated male population over 70 in 2040)	12.482	0.031	12.628	0.051	-0.146**	0.060	12.519	0.026
Log (Estimated female population over 70 in 2040)	12.812	0.0304	12.959	0.051	-0.148**	0.060	12.850	0.026
Training for regular care workers	0.686	0.018	0.745	0.028	-0.059*	0.034	0.701	0.015
Training for new regular care workers	0.508	0.019	0.628	0.031	-0.120***	0.037	0.539	0.016
Training for non-regular care workers	0.544	0.019	0.524	0.033	0.021	0.038	0.539	0.017
Training for new non-regular care workers	0.357	0.019	0.450	0.033	-0.093**	0.037	0.381	0.016
Perception on shortage of care workers	0.450	0.004	0.461	0.006	-0.012	0.008	0.453	0.003
Perception on shortage of nurses	0.220	0.004	0.231	0.007	-0.011	0.008	0.223	0.004
Perception on shortage of laborers	0.714	0.004	0.726	0.007	-0.012	0.008	0.717	0.004

Table 3. 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)
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, 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

VARIABLES	(1) Log(number of care workers)	(2) Log(number of nurses)	(3) Log(total number of employees)	(4) Log(monthly wage) - care workers	(5) Log(hourly wage) - care workers	(6) Log(monthly wage) - nurses	(7) Log(hourly wage) - nurses	(8) Log(monthly wage) - managers
Panel A. All employees								
Adopt robots	0.0429	0.0684**	0.0582*	-0.00443	-0.0120	-0.0106	-0.0477	0.000756
	(0.0324)	(0.0307)	(0.0352)	(0.0140)	(0.0100)	(0.0140)	(0.0314)	(0.0311)
Observations	857	857	857	6,805	1,685	1,307	202	650
R-squared	0.429	0.506	0.386	0.590	0.314	0.507	0.788	0.426
Panel B. Regular employees								
Adopt robots	0.0306	0.0680*	0.0470	-0.00527		-0.0134		
	(0.0395)	(0.0361)	(0.0376)	(0.0136)		(0.0138)		
Observations	857	857	857	6,360		1,251		
R-squared	0.408	0.476	0.397	0.569		0.466		
Panel C. Non-regular employees								
Adopt robots	0.0798	0.0414	0.0848		-0.0117		-0.0517	
	(0.0553)	(0.0522)	(0.0524)		(0.0098)		(0.0313)	
Observations	857	857	857		1,674		196	
R-squared	0.254	0.212	0.282		0.314		0.786	
Worker characteristics				Yes	Yes	Yes	Yes	Yes
Base facility characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Management practices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	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. Robot adoption and staffing – IV Estimates

VARIABLES	(1) Log(number of care workers)	(2) Log(number of nurses)	(3) Log(total number of employees)	(4) Log(monthly wage) - care workers	(5) Log(hourly wage) - care workers	(6) Log(monthly wage) - nurses	(7) Log(hourly wage) - nurses	(8) Log(monthly wage) - managers
Panel A. All employees								
Adopt robots	0.278***	0.388***	0.255**	-0.0291	-0.0599	-0.269***	0.0592	0.182
	(0.0737)	(0.125)	(0.106)	(0.0487)	(0.0523)	(0.0702)	(0.122)	(0.115)
Observations	857	857	857	6,805	1,685	1,307	202	650
First stage F-statistic	73.486	73.486	73.486	61.858	75.554	48.92	5.425	54.983
Panel B. Regular employees								
Adopt robots	-0.0780	-0.00082	-0.0418	-0.0279		-0.221***		
	(0.121)	(0.115)	(0.135)	(0.0496)		(0.0617)		
Observations	857	857	857	6,360		1,251		
First stage F-statistic	73.486	73.486	73.486	72.689		53.215		
Panel C. Non-regular employees								
Adopt robots	1.062***	0.784***	0.76***		-0.0586		0.0609	
	(0.167)	(0.264)	(0.145)		(0.0516)		(0.121)	
Observations	857	857	857		1,674		196	
First stage F-statistic	73.486	73.486	73.486		74.718		6.43	
Worker characteristics				Yes	Yes	Yes	Yes	Yes
Base facility characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Management practices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Labor shortage perceptions	Yes	Yes	Yes	Yes	Yes	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, 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. IV results by robot type

VARIABLES	(1) Log(number of care workers)	(2) Log(number of nurses)	(3) Log(total number of employees)	(4) Log(monthly wage) - care workers	(5) Log(hourly wage) - care workers	(6) Log(monthly wage) - nurses	(7) Log(hourly wage) - nurses	(8) Log(monthly wage) - managers
Panel A. Regular employees								
Monitoring robots	-0.113	-0.00119	-0.0605	-0.0410		-0.316***		
	(0.173)	(0.167)	(0.194)	(0.0714)		(0.0947)		
Observations	857	857	857	6,360		1,251		
First stage F-statistic	63.404	63.404	63.404	32.374		32.655		
Aid robots	-0.216	-0.00228	-0.115	-0.0679		-0.681**		
	(0.337)	(0.318)	(0.374)	(0.126)		(0.256)		
Observations	857	857	857	6,360		1,251		
First stage F-statistic	58.172	58.172	58.172	44.871		18.356		
Mobility robots	-0.395	-0.00417	-0.212	-0.127		-0.844*		
	(0.617)	(0.583)	(0.688)	(0.235)		(0.459)		
Observations	857	857	857	6,360		1,251		
First stage F-statistic	7.989	7.989	7.989	6.8		5.394		
Panel B. Non-regular employees								
Monitoring robots	1.538***	1.135***	1.100***		-0.0868		0.0736	
	(0.262)	(0.378)	(0.225)		(0.0777)		(0.139)	
Observations	857	857	857		1,674		196	
First stage F-statistic	63.404	63.404	63.404		39.066		20.04	
Aid robots	2.936***	2.168***	2.101***		-0.109		0.0671	
	(0.601)	(0.656)	(0.503)		(0.102)		(0.128)	
Observations	857	857	857		1,674		196	
First stage F-statistic	58.172	58.172	58.172		61.205		22.13	
Mobility robots	5.380**	3.972**	3.849***		-0.574		0.940	
	(2.264)	(1.859)	(1.375)		(0.607)		(3.864)	
Observations	857	857	857		1,674		196	
First stage F-statistic	7.989	7.989	7.989		1.76		0.08	

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, 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 7. Wage share and revenue growth

VARIABLES	(1) OLS Wage share (%)	(2) 2SLS Wage share (%)	(3) OLS Revenue growth (%)	(4) 2SLS Revenue growth (%)
Panel A. Adopt any robot				
Adopt robots	0.589	-7.705**	-1.109	-4.369
	(0.871)	(3.086)	(0.951)	(3.949)
Observations	779	779	802	802
R-squared	0.095		0.084	
First stage F-statistic		83.09		68.145
Panel B. Robot adoption by type				
Aid robots	1.064		0.105	
	(1.373)		(1.482)	
Mobility robots	0.339		0.877	
	(1.328)		(1.632)	
Communication robots	-0.119		-1.467	
	(0.979)		(1.182)	
Observations	779		802	
R-squared	0.095		0.084	
Panel C. Robot adoption by time				
Robot first adopted before 2017	0.802		-1.177	
	(0.908)		(0.997)	
Robot first adopted in 2017	-0.747		-1.719	
	(1.862)		(1.847)	
Observations	779		802	
R-squared	0.095		0.084	
Base facility characteristics	Yes	Yes	Yes	Yes
Resident case-mix	Yes	Yes	Yes	Yes
Other technology adoption	Yes	Yes	Yes	Yes
Management practices	Yes	Yes	Yes	Yes
Prefecture characteristics	Yes	Yes	Yes	Yes
HR development practices	Yes	Yes	Yes	Yes
Labor shortage perceptions	Yes	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, 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 8. Retention and foreign workers

	(1) Retention is difficult	(2) Hire foreign workers	(3) Plan to hire foreign 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, 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