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ROBOTS AND LABOR IN NURSING HOMES

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ABSTRACT

How do employment, tasks, and productivity change with robot adoption? Unlike manufacturing, little is known about these issues in the service sector, where robot adoption is expanding. As a first step towards filling this gap, we study Japanese nursing homes using original facility-level panel data that includes the different robots used and the tasks performed. We find that robot adoption is accompanied by an increase in employment and retention and the relationship is strongest for non-regular care workers and monitoring robots. The share of specific tasks performed by robots increases with the adoption of the respective type of robot, leading to reallocation of care worker effort to "human touch" tasks that support quality care. Robots are associated with improved quality (reduction in restraint use and pressure ulcers) and productivity.

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I. Introduction

Many service sectors rely heavily on the young and middle-aged workers increasingly scarce in aging economies, and face limited opportunities for offshoring or increasing reliance on immigrant labor.[1] Indeed, as many as 18 out of 36 OECD countries will experience declining populations by 2055 (United Nations 2017). Robotic technologies, originally developed for and widely adopted by manufacturing firms, have become increasingly common in many service organizations. Though robots often prompt concerns of job replacement, countries far along in the demographic transition like Japan increasingly view robots as key for augmenting a declining working-age population and alleviating the shortage of workers.

How do employment, tasks, and productivity change with robot adoption? Unlike manufacturing, little is known about these issues in the service sector, where robot adoption is expanding. As a first step into the analysis of the service tasks that robots perform, we study robots and labor in Japanese nursing homes. We collect original panel data to investigate the different robots used in nursing homes, the specific tasks they perform, their interactions with workers and other users, and the implications of robot adoption for staffing, quality, and productivity.

Shortages of workers have been especially salient in elderly care. In many countries, nursing homes experience persistent staff shortages and high levels of turnover as the elderly population and demand for caregiving services grows.[2] Nursing home care workers assist elderly residents with their daily activities, such as eating, exercising, bathing, toileting, and providing specialized care to residents with dementia or limited mobility. As such, care work in nursing homes is a physically and emotionally challenging job, but the pay is low (comparable to that of many service sector jobs that are not skill-intensive). The Covid-19 pandemic and the high number of cases and deaths in nursing homes have underscored the challenges of consistent, high-quality staffing and care for the elderly.

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[1] Immigrants often work in physically demanding positions such as care work. Giuntella et al. (2019) show that immigration leads to reallocation of native workers to jobs with lower physical burden and injury risk.

[2] For example, the US administration has called for new national legislation to establish a minimum nursing home staffing requirement because "the adequacy of a nursing home's staffing is the measure most closely linked to the quality of care residents receive" (The White House, February 2022, "Fact Sheet: Protecting Seniors by Improving Safety and Quality of Care in the Nation's Nursing Homes.") See also National Academy of Sciences, Engineering, and Medicine 2022.

Japan provides an especially relevant case to study for several reasons. First, Japan leads the world in terms of population aging and growing demand for long-term care (LTC) relative to a declining working-age population. Second, Japan is among world leaders in robotic technology and has been proactively developing and deploying robots in nursing homes to mitigate staffing challenges. Third, Japan's LTC insurance system provides a setting of a regulated service sector with widespread adoption of robots that may provide insights about how tasks have changed and how care processes have been re-engineered for worker and resident well-being. Japan's case can thus shed light on the debate surrounding new automation technologies and their implications for workers providing care to an aging population.[3]

We conducted two waves of surveys of Japanese nursing homes in early 2020 and 2022 to collect detailed information on robot adoption, staffing, quality of care, other technology adoption, and management practices. In the second wave, we also collected information on exposure to Covid-19 and the extent to which nursing homes use robots for various tasks. In designing the survey, we focused on themes that are central to deepening our understanding of the implications of automation technologies for workers and long-term care.

The first theme is the task share of automation. Canonical models of automation and jobs (Acemoglu and Autor 2011, Acemoglu and Restrepo 2018) posit a task-based framework where automation technologies replace tasks performed by humans. However, few studies (other than small time-and-motion studies like Kato et al. 2021) have collected task-level data to quantify the extent to which robot adoption changes worker effort on specific tasks. We identified the key tasks performed by care workers in nursing homes, and for each task asked how the share performed by robots versus humans has changed over the 2-year period, allowing us to construct "task automation indexes" by task type. Second, firms adopt a variety of robots that perform different tasks. Examining robot heterogeneity is important to gain a fuller understanding of the implications of robots for care work. In nursing homes some robots directly interact with and primarily assist the care workers; some robots are used by and primarily assist the residents; and other robots assist both residents and care workers throughout the facility. We distinguished three categories: monitoring robots, mobility robots, and transfer robots. Monitoring robots are

[3] Though Japan had already been using robots in nursing homes pre-pandemic, the pandemic accelerated robot adoption in nursing homes and hospitals around the world (Bloom and Prettner 2020), making Japan's experience even more relevant.

the most widely adopted type of robot; they assist care workers by providing real-time information about residents, as well as assist residents in communicating with care workers and family members, thus helping to mitigate loneliness. Mobility robots assist residents with daily physical activities, such as moving, toileting, and bathing. Transfer robots are used by the care worker to assist in lifting, repositioning, and transferring the residents (e.g., from bed to wheelchair). We survey the different types of robots to better reflect the nature of tasks they perform, and capture differences in adoption, price, and technological development.

Lastly, different robots may substitute or complement workers differentially. For example, transfer robots are specifically designed to reduce physical strain on care workers and require direct operation by human workers. These collaborative care robots are intended to augment the care workers rather than directly replace them, at least in the short term, and can potentially improve worker retention. In addition, some workers are on more stable employment contracts with benefits, and other workers are on more flexible contracts with fewer benefits, and often lower pay. In our context, a primary distinction is between what are called "regular" and "non-regular" workers, with the latter often working part-time with fixed-term contracts and receiving fewer benefits.[4] We survey the staffing levels of these two worker types, as well as their wages by experience level.

Analyzing the resulting survey data for a panel of nursing homes, we find that robot adoption has significant implications for care worker staffing, care task automation, and productivity. First, robot adoption is positively associated with both care worker and nurse staffing, especially non-regular workers. The complementarity between robot adoption and nursing home staffing is most prominent for monitoring robots. The complementarity between robots and staffing could be driven by robots alleviating care worker's physical burden and demands on their time, thereby improving the perceived work amenities at a given facility and reducing the persistent staffing shortages that facilities face. Indeed, we find that workers' exit rate decreases with robot adoption. This reduction in staff turnover arises in part by attracting and retaining additional non-regular workers.

[4] The literature has examined the heterogeneous effects of automation on workers by education or wage levels (e.g., Aaronson and Phelan 2022, Graetz and Michaels 2018) or by occupation (Dixon et al. 2021); relatively fewer studies examine differences based on contract type such as regular vs. non-regular or full-time vs. part-time work.

Second, to better understand the mechanisms underlying the staffing results, we examine tasks directly to see if staffing changes are accompanied by changes in task automation. We identified key tasks performed by care workers in nursing homes and for each task asked what share is performed by care workers versus robots. These tasks generally align with the three types of robots we described above. Accordingly, we grouped tasks into monitoring and communications tasks, mobility-related tasks, and transfer-related tasks. Robot adoption is significantly associated with an increase in the share of each task performed by robots. Moreover, the tasks being automated align with the type of robot adopted. Despite the current relatively low average levels of automation for nursing home tasks, robots clearly do take over a portion of each task. Examination of the relationship between staffing and task automation shows that higher levels of task automation are positively correlated with higher care worker employment, with magnitudes larger for non-regular care workers.

Third, we examine whether the positive relationship between robot adoption and staffing is accompanied by nursing home productivity improvements in terms of the quantity and quality of care. We find that monitoring robots and transfer robots are positively related to the number of residents receiving care, nursing home revenue, and the length of the waitlist to enter the facility. Furthermore, use of restraints and cases of pressure ulcers both decrease with robot adoption, especially monitoring robots, indicating improved quality of care and increased consumer (resident) welfare. The positive relationship between robots and productivity can arise because robots enable workers to devote more time and activity to caregiving tasks, which may directly improve quality of care. Moreover, care worker turnover is negatively associated with quality (Gandhi and Grabowski 2021, National Academies of Sciences, Engineering and Medicine 2022); the lower turnover in robot-using homes can improve the continuity and timeliness of care (e.g., through greater care worker knowledge of residents' needs and fewer gaps in service). However, we also find that mobility robots are associated with an increased number of falls. This may point to the potential problems that could arise when vulnerable residents attempt to use a new technology and become more mobile with the help of robots.

Our paper contributes to several strands of the literature. Though robot adoption has been expanding in the service sector (International Federation of Robotics, 2021), few studies use establishment-level data to examine the relationship between robot adoption, employment, tasks, and productivity in the service sector. To our knowledge, most of the existing studies are either industry-level studies (Dauth et al. 2021, Mann and Puttmann 2023, Adachi et al. 2024) or qualitative studies (Quershi et al. 2014, Sostero et al. 2020). We contribute to the literature by focusing on an increasingly important segment of the service sector, LTC in nursing homes. Our focused survey and panel data allow us to examine not simply whether facilities adopt robots, but each type of robot they adopt, the cumulative number purchased, and how that has changed over recent years. By delving into the heterogeneity of robot types, workers affected, and the changing share of specific daily tasks shared between robots and workers, we open up the black box of technology adoption that could be considered a key limitation in the economics of automation literature.[5] While numerous economics and management studies have explored the theoretical and empirical implications of robots, evidence regarding the service sector is scarce relative to the extensive research on industrial robots. For example, reduction in physical burden of various work tasks and thus improvement in worker safety and health has been demonstrated for industrial robots (Gihleb et al. 2022), but not yet for robots in the service sector. Our panel survey also collected detailed information on regular and nonregular nurses and care workers, including turnover (hiring and exits) and wages by experience level, as well as information about full-time equivalent staffing levels. Moreover, we examine how the tasks performed by humans and robots change with robot adoption. Empirically examining whether tasks change as predicted by task-based models (Acemoglu and Autor 2011, Acemoglu and Restrepo 2018) has been challenging, in part because of the fine-grained nature of the data required to examine tasks. To the best of our understanding, our paper is one of the first to examine different robots being used in an organization in relation to the specific tasks performed by robots and users.

In addition, we contribute to the literature by studying how nursing home productivity changes with robot adoption. To our knowledge, others have not yet analyzed service quality and

[5] Studies that examine the effects of industrial robots at an aggregate level have found varied results. For instance, Graetz and Michaels (2018) and Acemoglu and Restrepo (2020) find negative aggregate labor market impacts from industrial robots across countries and in the US, respectively. However, Chung and Lee (2023) find that the local labor market effects evolve and become positive in more recent periods, and Adachi et al. (2024) find that industrial robot adoption in Japan increases employment and scale of output. These findings point to the importance of firm-level evidence and detailed robot adoption data for unpacking when and why technology replaces or augments labor (Raj and Seamans 2019). Some of the recent firm-level or worker-level studies have found positive productivity (Bonfiglioli et al. 2024) or employment effects (Humlum 2022; Koch, Manuylov, and Smolka 2019; Acemoglu, Lelarge, and Restrepo 2020) and some have found the effects to be varying by worker type (Bessen et al. 2023, Dixon et al. 2021), or across industries (Dauth et al. 2021). Our paper adds to this body of literature on the relationship between new automation technologies, labor markets and firm productivity.

robot adoption over time. Compared to industrial goods, measuring quality and productivity is more challenging in the service sector, since quality is multi-dimensional and imperfectly measured, and often the output is non-tradable and scaling up is constrained by capacity and regulation. Assessing the productivity or value-added of nursing homes has been a long-standing challenge (Einav, Finkelstein, and Mahoney, 2022). Our approach is to examine both the quantity and quality of service with metrics tailored to those most often used for LTC services. In the context of nursing homes, measures of care quantity include the number of residents admitted (up to a facility's capacity), and the length of the waitlist. For quality of care, we collect data on health outcomes critical to resident well-being, such as restraint use, pressure ulcers, and falls resulting in injury.

Our study also contributes more specifically to the economics literature on nursing homes and the labor markets for those providing LTC services. Health economics research has studied nursing home staffing and its relationship to quality of care (Zhang and Grabowski 2004, Castle 2008, Grabowski et al. 2013, Lin 2014, Foster and Lee 2015, Hackmann 2019, Einav et al. 2022). Several studies probe factor substitution in production of LTC services, such as substitution between nurse staffing and other staff or material inputs such as psychoactive drugs (Cawley, Grabowski, and Hirth 2006). Ours is the first to study factor substitution between robots and direct care staff in nursing homes. We contribute empirical evidence from a setting relatively understudied in the economics literature: LTC in Japan, the country with the oldest population age structure in the world and tight labor markets, which provides a unique lens into the future strains many aging economies will face.

II. Robots in Nursing Homes and Long-term Care in Japan

II.1 Nursing Care Robots

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 Ministry of Health Labor and Welfare defines a nursing care robot as a form of robot technology that either directly aids care workers or helps the frail resident become more independent. Furthermore, the ministry 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. In our analyses, we group the robots into three main categories: transfer aid robots, mobility robots, and monitoring/communication robots.

Figure 1 provides an illustration of the different types of robots. Appendix Figure 1 show examples of robots being used in nursing homes. Transfer robots help with the lifting and transporting of residents, such as rotating residents on the bed, or lifting residents to transfer to a different bed, room, or wheelchair. These robots can be either worn by the care worker (wearable) or a stand-alone machine operated by the care worker (non-wearable). Non-wearable transfer robots can be large, creating challenges for storage and operation in facilities with limited available space. Mobility robots are used by the residents to assist in their mobility and aim to help the user become more independent so that they do not have to be as dependent upon caregiver support. Robots in this category can help residents with activities that involve physical movement, either during rehabilitation or to reduce the limitations imposed by permanent functional loss. Operating mobility robots effectively and safely requires some instruction and familiarity.

Monitoring robots remotely monitor residents' safety. Monitoring robots typically feature video devices or bed pads that use sensors to evaluate resident mobility and sleep patterns. Although they may not look like the stereotypical robot, they do have the three characteristics of a robot and operate as an integrative technology to assist both by care workers and residents. Comprised of sensors in rooms and on beds that detect and respond to the movements of the resident, these robots share information with care workers relevant for resident safety, such as danger of falling out of bed. Communication robots can initiate conversations and aim to promote verbal skills and reduce cognitive decline and well as enable the elderly to communicate with care workers. This category also includes companion robots, such as robot pets that help assuage loneliness.

II.2 Long-Term Care and Care Workers

Japan implemented universal LTC insurance starting in year 2000.[6] The insurance covers eligible citizens above age 40, evaluated for care need levels, covering payments to care providers for day-care services, in-home services, and residential nursing homes. The levels of care required are described in the appendix ("*Kaigo* Neediness Index"); they vary from level 1

[6] Please see Fu et al. (2023) for additional institutional details.

("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"). Similar to the healthcare and elderly care sectors of most high-income countries, the government regulates public LTC service prices. In Japan, these prices are uniform across nursing homes with small regional variations. 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 below). Facilities can expand their capacity over the long run and compete for residents based on location, convenience, and perceived quality of care services, shaped by local demographics and government regulations restricting the growth of public nursing home capacity (Sugawara 2017).

Japanese nursing homes by statute are all not-for-profit and are differentiated into two major types. The first, and the focus on our analysis, 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. Our data do not include the other type, the "*roken*" which resemble skilled nursing facilities in the US (i.e., providing intensive rehabilitation services for a few months, often after hospital discharge). Japan has a total of 2.2 custodial nursing homes per 100,000 population age 65 and older, with variation across prefectures (from 1 to 4 per 100,000). Occupancy rates are high (97% for custodial type, on average), and many homes have substantial waiting lists, indicating excess demand for care under the current regulated capacity system.

There are also two types of care workers entrusted with hands-on care for the residents of these facilities: care workers and nurses. The former assist residents with activities of daily living, similar to nurse aides in the US. Care workers are subject to three different levels of licenses in Japan but have minimal education requirements and are relatively low paid, as noted previously. Nurses perform a variety of clinical, rehabilitative and care 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. We denote the combined category of care workers and nurses (i.e., direct care staff) as "caregivers." Regulations in Japan require all 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.[7]

II.3 Demographic Challenges and Shortage of Care Workers

Because of Japan's below-replacement fertility, world-leading longevity, and therefore large and growing proportion of individuals aged 80 and older, the demand for long-term assistance with basic activities of daily living (such as eating, toileting, and bathing) is expected to continue to increase significantly. At the same time, the supply of care workers—those who provide direct contact care to older or disabled clients through assistance with tasks of daily living—may not grow to meet the demand; official projections indicate a shortfall of 380,000 care workers by 2025 (Ministry of Health, Labor and Welfare (MHLW) 2017). 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 (MHLW 2017, Eggleston et al. 2021). The shortage has been blamed on several factors, including that care workers are not well compensated and often experience physical repercussions such as lower back pain.[8] In particular, care worker wages barely exceed the minimum wage, in part because the prices for public LTC services are regulated and set low to control spending. The average hourly pay for care workers was 965 Yen in 2017, compared to the average minimum wage of 902 Yen.[9]

III. Data and Methods

III.1 Longitudinal Survey of Nursing Homes

We designed and fielded an original survey of nursing homes sampled from the universe of Japanese custodial-type nursing homes in late 2019, linked to administrative data on those same nursing homes. First, we collected some administrative data from a government website (https://www.kaigokensaku.mhlw.go.jp/) for all custodial nursing homes with capacity of at least 30 residents. From the universe of 7228 such facilities, we constructed a random sampling frame of 4000 nursing homes with full administrative data. Surveys were mailed in January 2020,

[7] For 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.
[8] 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.
[9] 100 Japanese Yen is approximately 1 USD. Source: Ministry of Health, Labor and Welfare (MHLW) 2017.

inviting respondents to participate in a research study on adoption and use of robots in nursing homes in Japan for the purpose of better understanding how to provide appropriate care to frail older adults despite a declining working-age and overall population. Respondent managers were provided with a summary sheet afterward but no financial incentives. In 2020, 848 nursing homes (21.2%) returned the survey. A follow-up survey with some added questions about tasks and COVID-19[10] was mailed to the same sample of 4000 nursing homes in January 2022, with a response rate of 14.2%, and matched to administrative data for those 569 nursing homes in 2022.[11] Our analytic sample consists of 265 nursing homes who responded to our surveys in both 2020 and 2022.

Our survey collects detailed information on robot adoption by type, other technology used in the facility (e.g., wifi, electronic medical record software, wheelchair lifts, intercoms, etc.), and management practices, which we modified to the LTC context from Bloom and Van Reenen (2007). In addition to staffing information, our survey collects quality of care data such as restraint use, pressure ulcer cases, and resident fall incidents. We believe our survey is one of the first to collect these nursing home quality measures in Japan. In the second wave, we also collected information on the extent to which robots were being used for various tasks in nursing homes. The task questions were adopted from O*NET descriptions to reflect care tasks conducted in Japanese nursing homes.

In addition to our survey, we also use the administrative data from the aforementioned government website. This data contains information on nursing home characteristics, including number of regular and non-regular nurses and caregivers, the number of residents by care level, capacity, facility location, and facility type (e.g., private, governmental, social corporation). We collected this data from the website in September 2019 and March 2022 and merged it with our panel survey data.

[10] The Covid-19 pandemic affected the elderly population most severely and was a major concern for nursing homes globally. The first wave of the survey was conducted in January 2020 before Covid-19 spread in Japan; our second wave, two years later, was conducted when pandemic-related public health measures were still in place. In wave 2, we asked nursing homes about Covid-19 cases and deaths, as well as vaccination status of residents and staff and pandemic protocols. 26.5% of nursing homes reported to have had a Covid-19 infection (either residents or employees) at their facilities. Among nursing homes with Covid-19 cases there were on average 2.9 infections and 0.4 deaths among the residents, and 2.7 infections and zero deaths among employees. Nearly all of the residents and employees (96.4% and 96%) were vaccinated.

[11] The study followed the appropriate IRB review procedures at Stanford University and the University of Tokyo.

On average, the nursing homes in our panel employ about 57 employees – including 40 caregivers (5 nurses and 35 care workers) – and have an occupancy rate of 98.4%, with capacity to care for 66.7 residents and 65.5 residents currently receiving care.[12] Compared to the population, these survey respondents represent slightly younger and smaller facilities with higher occupancy rates (i.e., half year less in operation and 6% lower capacity; see Table 1), but with virtually identical average age of residents (87 years old). Moreover, the number of full-time equivalent (FTE) care workers is similar (35.5 versus 36.2). According to the nationwide nursing home survey data in 2017, residential nursing homes that had acquired at least one robot were slightly larger with more staff than their non-adopting counterparts (Eggleston et al. 2021 Appendix Table 1). This is also the case in our survey (Table 3). Then, our panel of slightly smaller facilities may underestimate the prevalence of robot adoption in Japanese nursing homes and the extent to which tasks are shifting between humans and robots.

III.2 Robot Adoption in Nursing Homes

The use of nursing care robots has increased substantially in Japan's nursing homes over the past decade, as Japan's active robotics industry develops and refines the technologies for domestic use and export, supported by government policies. On the supply side, Japan's central government has subsidized development of nursing care robots, and on the demand side, sets aside funds for prefectural governments to improve LTC services, including subsidies for adopting nursing care robots.

In our 2020-22 panel sample, two-thirds of nursing homes had adopted at least one robot at baseline (January 2020), increasing to almost three-quarters of nursing homes two years later (Table 2 Panel A). Monitoring robots are the most common type of robot (used in 50.4% of nursing homes in 2020 and 63% in 2020); they help monitor whether individuals have gotten out of bed, fallen, or need assistance. Other common types are mobility robots to assist different residents at different times with movement, toileting and bathing, which were adopted by 17.9% of homes in 2020 and 26.4% of homes by 2022; and transfer aid robots to assist care workers with moving individuals such as from bed to wheelchair, for which the adoption rate increased from 18.7% to 25.7% between 2020 and 2022. The average nursing home in our sample had 10.3

[12] Although most nursing homes maintain long waitlists, occupancy rates are not 100% because of the frictions involved in resident turnover; once a bed becomes available, the resident has to make arrangements to move from the current residence to the facility, which often takes time.

monitoring robots, 1.3 mobility robots, and 1.0 transfer robot. In terms of the cost of robots, the monitoring robots are considerably cheaper and mobility robots most expensive. Based on our 2020 survey, nursing homes paid on average 202,000 Yen for monitoring robots, 424,000 Yen for transfer robots, and 1,680,000 Yen for mobility robots.

III.3 Care Task Automation

When designing the second wave of the survey we identified the tasks performed by Nursing Assistants (O*NET code: 31-1131) in the O*NET task descriptions and adopted those to reflect the Japanese nursing home context. We identified 11 key tasks performed by care workers in nursing homes and for each task asked what share is performed by care workers versus robots currently, and retrospectively 2 years ago. Respondents indicated these shares on a 1 to 5 Likert scale where 1 corresponds to "100% by care workers with no robots involved", 2 corresponds to "Mostly care workers, with some support from robots", 3 corresponds to "Care workers and robot both equally perform this task", 4 corresponds to "Mostly robot, with some guidance from care workers", and 5 corresponds to "100% by robots with no care workers involved." These tasks generally align with the three types of robots we described above. Accordingly, we grouped tasks into monitoring and communications tasks (monitoring residents during the day and night, answering resident calls or talking with residents for assistance), mobility-related tasks (assist residents in toileting, bathing, washing, undressing and dressing), and transfer-related tasks (turning and repositioning bedridden patients to avoid pressure ulcers, providing support to get out of bed or transfer to different locations). We constructed a task automation index defined as the average response across all tasks. We also constructed separate indexes for monitoring, mobility, and transfer tasks by taking the average response within the respective task group. The task automation indexes range from about 1.2 to 1.7, indicating that humans still perform the bulk of each task with a little bit of support from robots (Table 2 Panel B). Monitoring tasks are the most automated, followed by transfer tasks, and then mobility tasks. As expected, these tasks supporting and communicating with frail older adults are currently far from fully automated; yet there clearly has been an increase in the share of tasks performed by robots over time, augmenting and supplementing the role of care workers.[13]

[13] If we examine nursing homes that adopted the respective robots in 2022, we can further see that task automation is higher among these nursing homes: their monitoring task automation index is 1.97, mobility task automation index

III.4 Outcome Variables

In Table 3 we present the summary statistics of our key outcome variables for nursing homes that adopted robots (N=196), those that had not (N=69), and overall in 2022. The average nursing home in our panel sample employs 58.6 workers, with robot-adopting homes slightly larger than their non-adopting counterparts (59.7 vs. 55.8 total employees). Direct-care staff ("caregivers") include care workers and nurses, both of which can be either regular or non-regular employees. To capture the lower hours of part-time employees, we also analyze full-time equivalent (FTE) staffing. The average home employs 31.6 regular and 8.9 non-regular caregivers, totaling 35.6 FTE caregivers. Non-regular workers constitute about one-fifth of care workers and almost one-third of nurses in both robot-adopting and non-adopting homes. Robot-using homes employ slightly more nurses (5.3 vs. 4.8 in non-users) overall and in terms of FTE nurses (4.2 vs. 3.9), albeit representing the same proportion of FTE caregivers (11-12%) for both robot-adopting and non-adopting facilities.

Care worker turnover is a perennial problem that raises costs, constrains plans to expand, and potentially reduces quality of care. Therefore, we also analyze exits (mean 3.26) and new hires (mean 4.26) for care workers.[14] That the number hired over the previous 9 months to a year exceeds exits over that same period shows that facilities are still trying to fill vacancies from earlier exits, as well as seeking to expand in some cases.

We measure the quantity of care and associated revenue using the total number of residents cared for in the home,[15] and length of the waitlist relative to current capacity (which may also proxy for perceived quality). Robot-adopting homes average slightly lower revenue per employee than their non-adopting counterparts. The average home reports 105 people waiting for a vacancy in the home, with considerable heterogeneity (varying from 0 to 562). The number on the waitlist divided by the capacity of the home averages 1.58 with a large range -- meaning that the number on the waitlist varies from 0 to more than 13 times the capacity of the nursing home, with the average home in our sample having a waitlist 58% longer than the current capacity of

is 1.51, and transfer task automation index is 1.84.

[14] We lack turnover information for other employees, but since care workers are the most common direct-care staff and the ones in greatest shortage, analysis of their turnover should be indicative of this problem plaguing nursing homes.

[15] We create this variable by multiplying the LTCI monthly payment for each level of care required by the respective home's number of residents at that level, and then dividing by the total number of employees.

the home. The large heterogeneity in waitlist underscores the non-tradable, local market characteristics of this service, and that the constraints on expansion stem largely from the supply side—the tight labor market and policy regulation.

A distinctive feature of our data is relatively detailed information about several measures of residents' health, safety, and comfort that, when adjusted for the case-mix of residents, are often used to assess the quality of care in nursing homes. Most are problematic but difficult-to-avoid issues that may indicate low quality, such as using restraints to inhibit resident movement, pressure ulcers from bedridden residents not being moved or rotated frequently, and resident falls that may result in significant injury requiring medical care.

The number of residents restrained as of the day before the survey varies from 0 (for 80.8% of facilities) to 12, with lower use among robot-adopting facilities (17% reported any restraint use, compared to 26% among non-adopting homes).[16] We also collect data on the number of residents with pressure ulcers as of the day before the survey, which is reported positive for 62% of nursing homes, and varies from 0 to 18, with fewer cases in robot-adopting homes. Falls are also common; 71% of facilities reported that at least one resident had a serious fall during last nine months, ranging from 0 to 45 and averaging 2.68. Since monitoring robots may specifically mitigate falls at night when fewer care workers are present, we separately collect information on night-time falls, which are also not rare (39% of facilities report one or more). Robot-adopting homes report fewer falls overall and slightly more at night than their non-adopting counterparts. We added 1 to the value when analyzing in log form.

Our data includes wages of care workers with different levels of experience (0 or 5 years). Nonregular workers' hourly wages are less than the implicit hourly wage among regular (salaried, full-time) workers, and those with little or no experience earn only slightly above minimum wage. Those with 5 years of experience earn wages 9-18% higher than those lacking experience, and the monthly earnings of a salaried care worker with such experience is approximately equal to the payment a nursing home receives for caring for a medium-severity resident (care required level 3).

[16] This reporting of restraint use underscores that our respondents appear to be disclosing honestly, since they do report some use of restraints even though technically restraints are illegal in Japanese nursing homes in most cases.

Table 4 provides summary statistics of the facility-level and location-level control variables in our analytic sample, by robot adoption. Few characteristics display a statistically significant difference between robot-adopting and non-adopting facilities; both exhibit similar capacity, non-robotic technologies,[17] management practices, case mix of residents, Covid prevalence and prefecture characteristics, except that robot-adopting facilities own more standing-assistance lifts, have more residents at the highest care-need level, and employ more staff.

III.5. Empirical Framework

We investigate the relationship between robot adoption and nursing home operations with a panel regression of the following form:

$$Y_{it} = \beta Robots_{it} + X_{it}\Pi + \mu_i + \eta_{t,2022} + \varepsilon_{it}\ , \quad (1)$$

where Y_{it} represents various staffing or outcome measures of nursing home *i* in year *t* (e.g., staffing, task automation, turnover, quantity and quality of care). The primary variable of interest is the $Robots$ variable – either an indicator for robot adoption or ln(robots) for the current number of robots in use at the facility. Robot adoption is likely endogenous to staffing and quality of care. Our panel data and framework enable us to control for unobserved nursing home fixed characteristics and aggregate macro trends via nursing home fixed effects, μ_i, and a year fixed effect for 2022, $\eta_{t,2022}$. However, there will likely be time-varying characteristics that are associated with both robot adoption and staffing. We collect information on and control for many potential confounders. X_{it} represents the set of facility i's time-varying characteristics. Management practices are important for productivity of organizations, and will likely be related to robot adoption and staffing. Hence, we control for management practices by including variables that measure standardization of protocols, performance indicators, and promotion

[17] As noted, the Ministry of Health Labor and Welfare defines a nursing care robot as a form of robot technology that either directly aids care workers or helps the frail resident become more independent and has three characteristics: the ability to *sense information, make decisions based on that information, and take physical actions in response*. The other assistive technologies, such as lifting devices or adjustable beds, lack these three key features of a robot: they typically do not include sensors with any feedback loop to the human operator of the device, and none can use sensor information to take physician actions in response to assist the user or intended beneficiary. For example, while a lift device can reduce care worker back pain, it must be operated directly by the care worker, who must herself position the device and resident to operate the life safely and continuously sense the residents' position to adjust the lift device accordingly. A wearable transfer robot, in contrast, automatically augments the care worker and reduces the associated physical strain by sensing the careworker's muscle strain during each phase of the lift or transfer and/or the potential disequilibrium of the frail resident, and adjusting the muscle support and transfer process in response.

criteria. Nursing homes that adopt more (non-robot) technologies may also be more productive and employ more robots and care workers. We include dummy variables for other technologies used in the nursing home (e.g., electronic medical record software, wheelchair car lifts, etc.). Covid-19 may have encouraged robot adoption as well as directly impacted staffing. Hence, we also collected information on and control for whether the facility had any Covid-19 cases, the number of Covid-19 cases reported in the nursing home and in its locality (average number of cases in the locality excluding nursing home i). Also included in X_{it} are capacity and resident case mix (i.e., number of residents at different care need levels).

IV. Robots and Staffing

IV.1 Robots and Staffing in Nursing Homes

Table 5 presents results examining the relationship between robot adoption and staffing. Panel A reports estimates when only including nursing home fixed effects and the survey wave fixed effect. Panel B controls for nursing home capacity, other technologies being used in the nursing home, management practices, the case mix of residents, and Covid prevalence at the facility and region. The inclusion of facility and year fixed effects and the time-varying control variables helps to capture many correlated and potentially endogenous factors, although of course we cannot fully rule out omitted variables or other endogeneity concerns. Robot adoption is positively and significantly associated with overall employment and caregiver employment (i.e., care workers and nurses). The estimate in Panel B column (2) implies that any type of robot adoption at the nursing home is associated with about 6.5% increase in caregiver employment, or an increase of about 2.5 workers (from a base of around 38). Column (3) shows that the increase primarily comes from non-regular workers on flexible work contracts. To better understand the labor input changes from robot adoption, we examine full-time-equivalent (FTE) direct-care staffing levels in column (5). The estimates are negative and statistically indistinguishable from zero. Taken together this implies that the staffing increase associated with robot adoption results in the reduction of average hours worked per worker. The reduction in average hours per worker is also consistent with the increase in non-regular staffing.

We next examine how staffing changes with the number of robots in use. Two thirds of nursing homes had adopted some type of robot by 2020. Hence, for many nursing homes the variation in robot adoption is in the count of robots (the intensive margin) and the types in use, rather than whether or not it adopted any robots (the extensive margin). Panel C presents results for the intensive margin of robot adoption with only the nursing home fixed effects and the survey wave fixed effect. Panel D includes additional controls for time-varying nursing home characteristics. Focusing on the latter, we see that a ten percent increase in robots is associated with a 0.24% increase in total employment (column 1) and about a 0.3% increase in caregivers (column 2), with the relationship again being driven by non-regular workers (column 3). The coefficient estimate on the FTE staffing level is smaller in magnitude than that for the count of overall employees, consistent with reduction in average hours worked per worker and non-regular flexible work contracts driving the increase in staffing associated with more robot adoption.

The finding that robots are positively associated with staffing rather than negatively suggests that robots are not fully replacing care worker tasks, but rather complementing them. There may be several reasons why robots are associated with increased staffing. Some robots may free up care worker time from repetitive or rudimentary tasks, so that they may focus on activities more directly related to caregiving and allow care workers to spend more time with the residents. If this is the case, we would expect to see productivity improvements in terms of the quality of care. Also, robots may alleviate the physical burden of care, e.g., pain from burdensome lifting and assistance tasks, and reduce turnover and exits, which would help staffing when there is a constant shortage of care workers. We examine these dimensions in the ensuing empirical analyses.

IV.2 Care Staffing by Type of Robot

As noted, we categorize nursing care robots into three types: monitoring, mobility, and transfer robots. Table 6 shows that the complementary relationship between staffing and robots is driven by monitoring robots. Panel A examines the extensive margin (whether or not a robot was adopted) and Panel B examines the intensive margin (the number of robots in use). First focusing on the monitoring robots, we see that monitoring robot adoption is associated with about a 5.8% increase in caregiver staffing (Panel A column 2). A doubling in the number of monitoring robots (on average 7.7 devices in 2020) is associated with about a 3% increase in caregiver staffing, equivalent to about 1.2 more care workers or nurses (Panel B column 2). We observe qualitatively similar patterns with Table 5 regarding the difference in the magnitudes of coefficient estimates between non-regular and regular workers, as well as between gross and FTE staffing levels. However, the estimates on mobility and transfer robots are not significant. Thus, the complementarity between robot adoption and care worker staffing appears to be primarily driven by monitoring robots and complementarity is stronger for non-regular workers, where hiring increases the small base of non-regular workers (approximately 4 regular per 1 non-regular caregiver in our sample).

Why might staffing be especially sensitive to monitoring robots? On a per-resident level, monitoring robots are relatively low cost, as well as easy to store and use, and (as a result) widely adopted, with facilities typically purchasing multiple devices. On the other hand, mobility or transfer robots are comparatively expensive, bulky, and used for one resident at a time; the number in use naturally is lower. The new generation of monitoring robots that we examine uses computer vision or radio wave sensors to automatically adjust beds based on machine learning algorithms, building on older technologies such as telecoms or video monitors that have long been integral to daily operations. Hence the enhanced capabilities of monitoring robots can be seamlessly integrated into caregiving workflows. This familiarity enables nursing homes to use monitoring robots productively with lower learning costs, uncertainty, and experimentation. Transfer robots and mobility robots are relatively novel, with care workers and residents still experimenting with the best ways to incorporate these devices into their routines.[18]

To further probe the role of non-robotic technologies and the importance of our data distinguishing those technologies from robot adoption, Appendix Table 4 provides the full results on the association between staffing and nursing home characteristics, including use of non-robotic assistive technologies, as well as a falsification test excluding robot adoption. The

[18] Appendix Table 2 presents the staffing results from a pooled OLS regression without the nursing home fixed effects. Comparing to the corresponding panel estimates with controls in Table 5 Panel B, the pooled OLS estimates for any robot adoption (Appendix Table 2 Panel A) show the total employee and caregiver results are nearly identical, and the FTE equivalent results are both indistinguishable from zero. However, when we separately examine the non-regular and regular workers, the difference is more evident. The OLS estimates of 0.0567 and 0.049 are relatively similar, with the latter estimate for regular workers statistically significant. In the panel analysis, the estimates diverge, with the estimate for non-regular workers larger (0.137) and significant at the 5% level, whereas the estimate for regular workers is 0.02 and no longer significant. Also, when looking at monitoring robot adoption or number of robots in use (Appendix Table 2 panels B, C and D), the FTE estimate in the pooled OLS regression is similar to the total caregiver estimate, whereas the FTE estimate is significantly smaller than the total caregiver estimate in the panel regressions (Tables 5 and 6). These patterns suggest that the pooled OLS estimates primarily pick up the correlation between facility size and robot adoption, whereas the panel estimates capture the differential association of robots with employment of non-regular and regular workers, and for FTE compared to gross employment.

patterns of correlations of staffing variables with resident case-mix and other assistive technologies (e.g., positive association of staffing with carlifts and adjustable beds) are similar with and without the robot adoption variables; as expected, omission of robot adoption explains slightly less of the variation in staffing across facilities. Appendix Table 5 shows the piecewise correlation between robot adoption and each other technology, illustrating the relatively low correlation between specific non-robotic technologies and robots.

IV.3 Robots and Turnover - Hiring and Exits

If robots perform some of the arduous tasks performed by care workers in nursing homes, robot adoption may help reduce turnover. One of the key challenges for nursing home managers is the difficulty of recruiting and retaining staff, given shortages and high turnover among care workers. In Table 7 we examine how care worker hiring and exit rates change with robot adoption. The outcome variables are the number of care workers hired or who exited in the previous year, divided by the total number of care workers. Hence, we are examining how the flow of workers changed with robot adoption. We also examine regular and non-regular workers separately. In Panels A and B we see that robot adoption is consistently and negatively associated with exits. When disaggregated by robot type, we find that mobility robots drive the turnover results. Mobility robots directly support tasks performed by caregivers, especially the arduous and often physically demanding tasks of assisting residents with bathing and toileting. Shifting more of these tasks to robots may help reduce care worker turnover. Since adoption of mobility robots also usually comes after monitoring robots have already been adopted, they may signal a facility further along in the process of re-engineering workflows to mitigate the "pain points" for care workers. Thus, adoption of robots could be considered to supplement the work amenities for care workers, reducing exits and the associated costs of recruitment and training of new care workers. Because in LTC the consistency of care worker-resident interactions can be an important component of quality care, reduction in turnover may also directly contribute to better or more consistent attention to resident-specific quality and safety concerns.

V. Robots, Tasks, and Staffing

We next examine whether the share of tasks performed by robots increases with robot adoption and how staffing changes with task automation. Such a task-based analysis can shed light on the mechanism underlying the positive relationship between robot adoption and care staffing.

Table 8 examines how the share of tasks performed by robots is associated with robot adoption. Column (1) examines overall task automation, and the following columns each examine monitoring task automation, mobility task automation, and transfer task automation. Each dependent variable is an index constructed by averaging the responses across individual tasks. Panels A and B indicate that robot adoption both at the extensive and intensive margins is significantly associated with an increase in the share of tasks performed by robots across all tasks and within each task group. Despite relatively low average levels of automation for nursing home tasks, robots clearly do take over a portion of each task.

To further probe and corroborate the increasing share of tasks performed by robots, we examine whether task automation aligns with the specific types of robots designed to perform each set of tasks. Monitoring robot adoption would be associated with an increase in the share of monitoring tasks performed by robots, and similarly for mobility and transfer robots and tasks. Panels C and D present the results. We indeed find that the share of monitoring tasks performed by robots increases only with the adoption of monitoring robots. Similarly, the robot share of mobility tasks increases only with the adoption of mobility robots. For transfer robots and transfer task automation the results (Panel D) are positive and of similar magnitude (Panel B) but not statistically significant, indicating that robots are not yet substantially reducing heavy-lifting jobs that care workers perform every day. This may reflect the fact that transfer robots are the least commonly adopted (mean 1.2 in 2022), leaving us underpowered to detect significant associations. The finding that monitoring robot adoption is associated with an increase in transfer task automation (Panel C column (4)) is not anomalous, since monitoring robots and bed sensors are used to assist residents to adjust positions in their beds and when transferring out of them.

Overall, Table 8 confirms that robot presence in a nursing home indeed increases the share of relevant tasks performed by robots compared to care workers. This may constitute the first empirical evidence documenting that the share of tasks performed by robots relative to workers increases with robot adoption over time within the same organization.[19]

[19] Robots increase task automation at the intensive margin, that is by affecting the share of each task performed by robots versus humans, and not at the extensive margin, that is fully replacing humans to conduct a certain task.

In canonical task-based models (Acemoglu and Restrepo 2018, Acemoglu and Autor 2011), automation reduces labor demand when robots perform tasks previously done by humans. The task-based displacement effect can be countered by direct productivity gains from automation or creation of new tasks for labor. In our setting where robot adoption increases the share of specific tasks performed by robots without fully displacing workers from the task, robot adoption reduces the share of tasks performed by workers, which could result in a reduction of hours worked. Also, the fact the same tasks are performed by humans and robots implies that the two inputs can be collaborative and complementary.

Finally, in Table 9 we examine how staffing changes with task automation. A higher share of tasks performed by robots is positively correlated with more caregiver employment (Panel A Column (2)). The magnitude is larger for non-regular compared to regular workers, though both estimates are not statistically significant. The increase in full-time equivalent staffing from task automation in column (5) is smaller in magnitude than that of gross staffing in column (2). The pattern of estimates we find in Panel A is remarkably similar to that of robot adoption in Table 5. In Panel B we examine task automation separately for the three task groups. Staffing is significantly complementary with monitoring task automation, which is consistent with what we found for monitoring robots. The staffing and task automation results in Table 9 along with the task automation and robot adoption results in Table 8 suggest that robots play a pivotal role in the positive association between robot adoption and care staffing.

VI. Robots and Productivity – Quantity and Quality of Care

The staffing increases associated with robot adoption suggest that there may be productivity gains associated with robot adoption in nursing homes. Care workers may be able to perform arduous tasks more effectively by using the assistance of robots or better monitor and respond to resident needs. We examine productivity in terms of the quantity and quality of care. In the case of nursing homes, quantity of care improvements can be associated with an increase in the number of residents being cared for, up to each facility's capacity. In column (1) of Table 10 we examine robot adoption and the number of residents. Robot adoption is associated with slightly

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However, this could simply reflect the semantic differences about how narrowly or broadly one defines a "task", e.g., from the "task" of "monitoring residents" to the task of "monitoring movement between 1 and 2am." The context also matters. Robots may replace certain tasks outright in manufacturing, such as welding or painting, but in the service sector—and in particular the LTC sector—robots and humans are predominantly splitting tasks or complementing each other in performing various tasks.

over 2% increase in the number of residents (Panel A), an increase of one or two residents. Monitoring robots and transfer robots are primarily contributing to the increase in residents (Panel C), and the findings are consistent when we examine the number of robots in use in Panels B and D.

We examine nursing home revenue in column (2). Nursing home revenue is closely tied to the number of residents, since reimbursement for each resident is based on a fixed rate for the different care levels and is set by national LTC insurance. We construct the nursing home's revenue by multiplying the national average of LTC expenditure per resident in each care level by the number of residents in each care level in our nursing homes. Hence revenue can increase either when the number of residents increases or when the resident mix changes to higher care-level residents. We find that robot adoption is associated with an increase in revenue and the magnitudes are similar but slightly smaller when we simply examine total counts. This could imply that the mix of residents is changing to less intensive care-levels. However, we find that the coefficient estimate in column (2) is larger than that of column (1) for transfer robots, which would imply that the adoption of transfer robots is associated with an increase in high care-level residents. Since some facilities may be at capacity, we examine the waitlist for each facility. If robots improve quality of care, we expect to see a longer waitlist in facilities that have adopted robots. Indeed, robot adoption (especially, monitoring robot adoption) is significantly associated with an increase in the waitlist scaled by capacity (column 3). The quantity of care improvements with robot adoption also suggests a correlation between robot adoption and perceived quality of care at the facility, which is substantiated by actual metrics of care outcomes, the topic we turn to next.

Columns (4)-(7) of Table 10 directly examine several quality outcomes. We first examine restraint use. Nursing homes may restrain residents to prevent falls and injuries when left alone, sleeping, or at other times when care workers cannot continuously directly monitor the resident. However, physical restraints fundamentally infringe upon dignity and are advised to be avoided in all but the most extreme circumstances where the safety of the resident or care workers is at risk. Fortunately, robot adoption is associated with a 13% (Panel A column (5)) decline in use of restraints in nursing homes. In particular, the adoption of monitoring robots is associated with a decline in restraint use by about 18% (Panel C); the estimated association of restraints with mobility and transfer robots is also negative although indistinguishable from zero. When we examine the intensive margin, we continue to find negative coefficients, although the estimates are not statistically significant (Panels B and D). In column (6) we examine pressure ulcers, a key measure of low quality of care in nursing homes (Foster and Lee 2015). Many bed-ridden elderly residents, if not regularly rotated and repositioned, may develop pressure ulcers. Pressure ulcer incidence among residents drops by about 26% with robot adoption (Panel A), suggesting substantially higher quality.

Lastly, we examine falls in general, and falls during nighttime, as quality and safety concerns. Falls, especially nighttime falls, are negatively associated with monitoring robot adoption. However, there are significant positive associations between falls -- both overall and at night -- and the adoption and increased use of mobility robots. Frail elderly residents use mobility robots to help be independent and move around for various needs. However, lack of familiarity with the operation of the robots, combined with the physical frailty of the elderly user, may increase the number of falls and exacerbate safety concerns. Indeed, qualitative evidence supports this interpretation.[20]

VII. Additional Analyses and Robustness

VII.1 Results by Worker Type

In Table 11, we separately examine care workers and nurses, finding that both increase with robot adoption, and the estimate is larger for nurses compared to care workers (Panel A). This may indicate skill-biasedness in robot adoption in nursing homes; nurses are more skilled than care workers and robot adoption is more strongly associated with nurse staffing. It may also reflect the lower base number of nurses in a facility compared to care workers (5 nurses vs. 35 care workers). Again, the estimates for non-regular workers are larger than that for regular workers. FTE staffing increases for nurses (by about 8% of a base of 4 FTE nurses), but the change is statistically indistinguishable from zero for care workers. The estimates are smaller in magnitude compared to the corresponding gross count estimates in columns (1) and (5). For both care workers and nurses, non-regular employment contracts are the driver of staffing increases associated with robot adoption. Comparing the magnitude of the estimates for total employment and FTE employment shows that the reduction in average hours worked is considerably stronger

[20] Some nursing homes have reported that it is difficult to learn the settings and operations when a resident first starts using a mobility robot, and that it took several months before the users were able to set up and manage the system themselves (Ministry of Health, Labor and Welfare, 2018).

for care workers than for nurses. Again, care worker and nurse staffing changes are primarily associated with monitoring robot adoption both at the intensive and extensive margin. The pattern of estimates in Panels A and B is qualitatively similar when we examine robot adoption at the intensive margin in Panels C and D. [21] In Appendix Table 1, we report results on the occupation mix of direct-care staffing, measured as the ratio of nurses to care workers. Although estimates tend towards positive, we do not find any significant results on the occupation mix. The pattern is consistent with the results on nurse and care worker staffing results presented in Table 11.

VII.2 Robots and Earnings

We also examine how employee earnings change with robot adoption. We asked the survey respondent (nursing home manager or operator) to report care worker average earnings (monthly or hourly) for regular and non-regular care workers with no experience and 5 years of experience. We also asked the annual bonus amount for regular workers and incorporated into their wages. We asked the earnings information to be reported separately for the different types of contracts and each column in Table 12 represents the different contracts. The response rate to the earnings questions was lower so the sample size is smaller. We find that earnings are positively correlated with robot adoption, especially monitoring robot adoption for new regular care workers. However, for care workers with 5 years of experience we find a negative association between robot adoption and earnings. In particular, regular staff earnings decrease with mobility robot adoption and non-regular staff earnings decrease with monitoring robot adoption. Robots may be more complementary to less experienced workers, because younger workers may be more adept at using new technology or the capital costs incurred by adopting robots motivate facilities to reduce labor costs (of more expensive workers).[22] Indeed there seems to be less demand for more experienced care workers and more demand for less experienced care workers with robot adoption.[23]

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[21] Appendix Table 9 shows that the complementarity between task automation and caregiver staffing is concentrated among care workers rather than nurses. There is a marginally significant negative association between nonregular nurses and the task automation index.

[22] There is some parallel to this trend in other sectors. Collaborative robots and advanced robotics in manufacturing are increasingly designed to help unskilled workers perform tasks that had been the exclusive domain of experienced workers with years of accumulated experience in the craft. This endogenous technological innovation has been triggered by the shortage of experienced workers and the aging workforce in manufacturing and construction.

[23] See Appendix Table 6. In Appendix Table 6, we correlate labor share (measured as wage bill over revenue) to robot adoption, using the cross-sectional data collected in 2022. The estimates are all negative though not

VII.3 Robustness by Sampling Schemes

In the appendix, we also report a series of analyses exploring the sensitivity of results to different sampling schemes. The primary results are robust to limiting to a balanced panel of nursing homes where the number of robots in use is non-missing in both years, and a balanced panel of nursing homes where the number of robots in use is non-decreasing between the waves. The latter addresses the possibility of some nursing homes not actively using robots currently, despite having purchased them. Appendix Table 3 reports these robustness tests for total employment and caregiver staffing dependent variables; Appendix Table 7 shows the robustness tests for quality measures; and Appendix Table 8, the robustness of staffing and quality results by type of nursing care robot adopted. In each case, Panel A shows the balanced panel sample with non-missing information on the number of robots in use, Panel B the balanced panel sample with non-decreasing number of robots in use, and Panels C and D results for the subsample of nursing homes with resident capacity below and above the median (60 people), respectively.

VIII. Discussion

Analysis of our facility-level panel data of Japanese nursing homes reveals that robot adoption is accompanied by an increase in employment, with the relationship strongest for nonregular staff, although the majority of care workers remain regular full-time workers. The complementarity between robot adoption and staffing is primarily associated with monitoring robots. While several previous studies find employment increases in robot-adopting firms (e.g., Acemoglu, Lelarge, and Restrepo 2020, Dixon et al. 2021), most focus on manufacturing firms and/or tradable services and exports. We add evidence that establishments also increase employment alongside robots in the service sector. Mitigating the problem of high staff turnover, especially by improving retention of care workers, appears to be a primary change associated with (and perhaps motive for) robot adoption. Robot adopters can reduce the costs of worker turnover as demographic change reduces labor supply while increasing long-run demand. An additional finding related to staffing is that a rising share of care tasks performed by robots is positively correlated with higher employment of non-regular care workers. This pattern suggests

statistically significant. We thank an anonymous reviewer for suggesting this analysis, and plan to go beyond cross-sectional examination of labor share in future research.

that robots enhance the perceived working conditions for care workers and thus reduce attrition and the costs of turnover, while allowing deployment of nonregular workers to meet the staffing needs of current capacity as well as lay the foundation for future potential expansion. Indeed, we find waitlists increase in robot-adopting homes, so that they may be well placed to gain market share in the future, although the regulatory process makes such expansion slow.[24]

An important aspect of LTC is that staffing (employment) per customer is closely correlated with, and often proxies for, quality (Norton 2000, Castle 2008). The fact that we find that the number of full-time-equivalent direct-care staff increases apace with increases in residents already hints at the improvements in quality and productivity that we identify through direct measures of resident outcomes such as reduced use of restraints and pressure ulcers.

Monitoring robots are the type of robot most closely associated with both increases in care workers and reductions in use of restraints and pressure ulcer cases. These improvements in quality of care are also correlated with care workers opting to stay on the job longer, as manifest in lower exit rates. Achieving consistent staffing levels and reducing the quality problems associated with frequent care worker turnover are well known to contribute to better nursing care outcomes (National Academies of Sciences, Engineering and Medicine 2022). Moreover, to the extent that the observed lower exit rate stems from care workers perceiving robot adoption as a signal of a better workplace, greater worker job satisfaction may constitute an underlying mechanism for the productivity benefits. However, we also find that mobility robots are associated with more falls, indicating that technologies intended to expand autonomy and independence for frail residents can have negative side-effects for new users.

These findings regarding staffing and quality point to the change in tasks performed by workers and robots. Using our unique data, we document that in robot-adopting homes, an increasing share of care worker time and effort is focused on the "human touch" tasks that support quality care, while robots take over some automatable share of caregiving tasks. Specifically, for monitoring, communication, and transfer tasks, the share of tasks performed by robots increases with the adoption of the respective type of robot, leading to corresponding reduction in care worker effort on those tasks. Examining the specific tasks performed by robots

[24] Our data does not speak to whether sector-wide employment (rather than employment at adopting establishments) would be complementary to extensive robot adoption, although our results are consistent with the intent of policy to improve the attractiveness of care work as a profession to compete in a tightening labor market with other service sector jobs that are also relatively skill-non-intensive.

in nursing homes provides a unique but important context – important in its own right, and indicative of how robotic technologies can augment and automate tasks in services where human workers retain key comparative advantages. As societies age, the demand for LTC will undoubtedly grow, and Japan has been at the forefront of adopting robots to address staffing challenges. Robot adoption may signal to workers the managers' efforts to address their concerns about strenuous and back-wrenching tasks and improve retention, while allowing workers to focus on tasks that improve quality of care.

Overall, our empirical results suggest that many of the findings about enhanced productivity found across industrial and broader service sectors (e.g., Dixon et al. 2021) may also hold for regulated healthcare markets and other settings where prices are regulated in the output market but not for inputs (such as wages). We also enlarge the scope of organizational forms studied in the literature, given the prevalence of nonprofits in publicly-financed services like healthcare and elderly care.

Despite these contributions, our study must also be interpreted with caution. The data stems from a relatively small sample of nursing homes that responded to both waves of our survey, and reflect a setting where all providers are not-for-profit. There will be value in following technology use for specific tasks in a larger sample of facilities over time and comparing to other sectors and countries, to better understand how generalizable these patterns are. Moreover, although we control for a relatively rich set of facility-level characteristics as well as facility fixed effects, our analyses cannot pin down causality, a task left to future research. Finally, it remains unclear how collecting this data during the COVID-19 pandemic may shape the findings. While the pandemic may have accelerated technology adoption globally and robotics in the service sector specifically (Bloom and Prettner 2020), other factors may have pushed towards decelerated adoption and investment in the complementary task-reengineering that spur productivity improvements from robot adoption. For example, during the acute phase of the pandemic, Japan was closed to immigrant labor, which may be important factor in the null results regarding hiring.[25] Nevertheless, Japan and many other aging economies will continue to

[25] Although the reduction in rate of nursing home entry during the pandemic was lower in Japan than many other countries more significantly affected by the pandemic, the longer-term relationship between robots and waitlists or capacity may differ from this period. Abe and Kawachi (2021) identify smaller-unit-based nursing homes and higher wages (and thus the higher care worker-to-resident ratios) as key differences in how Japan succeeded in containing COVID-19 compared to the US.

face tight labor markets and increasing demand for LTC, suggesting a long-term trend toward supplementing more caregiving tasks with robotic technologies.

IX. Conclusion

How do staffing, tasks performed by care workers, and productivity change with robot adoption in nursing homes? To probe this question, we conducted surveys of nursing homes in early 2020 and 2022 in Japan, linked to administrative data on nursing home characteristics. We separately examine three types of nursing care robots: monitoring and communication robots; mobility robots that assist residents with walking and bathing; and transfer robots that assist care workers in lifting, repositioning, and transferring bed-ridden residents. This data helps fill a gap in the economics literature on automation and workers: namely, that diverse robotic technologies are usually measured as a single 'robot' category, often lacking the granularity needed to capture the different functions and types of robots being used, who primarily interacts with them, and how tasks are split between robots and workers. Our paper, to the best of our knowledge, is the first to investigate the relationship between different robots employed within an organization and the specific tasks they perform, their interactions with users, and ultimately, how staffing and productivity change with robot adoption.

In our panel of Japanese nursing homes, robot adoption complements care workers by reducing quit rates, and is associated with better quality of care. These patterns suggest that robots can potentially improve productivity by shifting the tasks performed by care workers towards those involving human touch, empathy and dexterity where workers retain a comparative advantage. Different robots differ in complementarity depending on the primary user or beneficiary (i.e., care worker or frail resident). Although some robots may raise safety concerns for users not well trained to operate them, robots are also associated with important metrics of quality in long-term care, such as reduced use of restraints and fewer pressure ulcers among frail elderly. Overall, our findings suggest that robots can help reduce strain and shortages among care workers and improve quality and productivity, and that different types of robots have different degrees of complementarity with specific workers and tasks.

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Figure 1. Types of Nursing Care Robots

Transfer Robots

Wearable

Wearable equipment that uses robotic technology to provide power assistance to care workers

Non wearable

Non-wearable equipment that uses robotic technology to provide power assistance for lifting movements by care workers

Mobility, Toileting, Bathing Robots

Robotic equipment to support mobility (outdoors and indoors), toileting, and bathing for older people.

Monitoring and Communication Robots

Communication

Lifestyle support equipment using robot technology to communicate with older people.

Monitoring

Robotic equipment with sensors and external communication functions to watch over older people in nursing homes.

Source: Authors' translation of Ministry of Economy, Trade and Industry document

Table 1. Sample Comparison

	Panel sample (N=265)		Remaining population sample (N=6,963)		t-test
VARIABLES	mean	SE	mean	SE	p-value
Total employees	57.19	1.15	60.06	0.27	0.038
Caregiver (care worker or nurse)	39.81	0.91	41.66	0.20	0.082
Caregiver, regular	31.46	0.68	31.15	0.15	0.694
Caregiver, non-regular	8.351	0.45	10.52	0.11	0.000
Caregiver-FTE	35.45	0.82	36.23	0.18	0.397
Care worker	34.74	0.85	36.19	0.19	0.141
Care worker, regular	27.89	0.64	27.51	0.14	0.614
Care worker, non-regular	6.853	0.40	8.677	0.10	0.000
Care worker-FTE	31.31	0.77	31.82	0.16	0.546
Nurse	5.069	0.12	5.474	0.03	0.004
Nurse, regular	3.571	0.08	3.634	0.02	0.514
Nurse, non-regular	1.498	0.12	1.840	0.02	0.007
Nurse-FTE	4.140	0.08	4.404	0.02	0.010
Capacity (max. number of residents)	66.72	1.42	70.73	0.34	0.022
Number of residents	65.57	1.39	68.76	0.33	0.062
Occupancy rate (# of residents/capacity)	0.984	0.00	0.974	0.00	0.023
Average age of residents	87.16	0.11	87.13	0.11	0.952
Years in operation	20.12	0.72	20.53	0.15	0.064

* Population of 7,228 nursing homes, less those included in the analytic sample of nursing homes who responded to both waves of the survey ("panel sample").

Table 2. Robot adoption and task automation

	2020			2022			Total		
	Mean	SE	N	Mean	SE	N	Mean	SE	N
Panel A. Robot adoption									
Robot adoption (any)	0.667	0.030	252	0.740	0.027	265	0.704	0.020	517
Adopt monitoring robots	0.504	0.032	252	0.630	0.030	265	0.569	0.022	517
Adopt mobility robots	0.179	0.024	252	0.264	0.027	265	0.222	0.018	517
Adopt transfer robots	0.187	0.025	252	0.257	0.027	265	0.222	0.018	517
Number of robots in use	9.468	0.954	235	15.51	1.517	254	12.61	0.921	489
Number of monitoring robots in use	7.732	0.834	235	12.63	1.270	254	10.28	0.779	489
Number of mobility robots in use	0.851	0.245	235	1.689	0.595	254	1.286	0.331	489
Number of transfer robots in use	0.851	0.280	235	1.185	0.227	254	1.025	0.179	489
Panel B. Task automation									
Task automation index	1.439	0.032	235	1.465	0.030	259	1.453	0.022	494
Monitoring task automation index	1.646	0.043	235	1.676	0.041	259	1.662	0.030	494
Mobility task automation index	1.233	0.031	234	1.246	0.029	258	1.240	0.021	492
Transfer task automation index	1.318	0.037	233	1.357	0.034	258	1.338	0.025	491

Table 3. Summary statistics of key outcome variables

	Adopted			Not adopted			Total		
VARIABLES	mean	std.err	N	mean	std.err	N	mean	std.err	N
Total employees	59.66	1.45	196	55.77	2.01	69	58.64	1.20	265
Caregiver (care worker or nurse)	41.15	1.10	196	38.31	1.70	69	40.41	0.93	265
Caregiver, regular	32.10	0.84	196	29.96	1.30	69	31.55	0.70	265
Caregiver, non-regular	9.04	0.55	196	8.35	0.85	69	8.86	0.47	265
Caregiver-FTE	36.11	0.97	196	34.05	1.46	69	35.58	0.81	265
Care worker	35.80	1.02	196	33.54	1.59	69	35.21	0.86	265
Care worker, regular	28.44	0.79	196	26.78	1.24	69	28.01	0.67	265
Care worker, non-regular	7.37	0.47	196	6.75	0.76	69	7.21	0.40	265
Care worker-FTE	31.88	0.91	196	30.10	1.36	69	31.42	0.76	265
Nurse	5.34	0.17	196	4.77	0.19	69	5.19	0.13	265
Nurse, regular	3.67	0.10	196	3.18	0.18	69	3.54	0.09	265
Nurse, non-regular	1.67	0.17	196	1.59	0.19	69	1.65	0.13	265
Nurse-FTE	4.24	0.10	196	3.94	0.17	69	4.16	0.09	265
New hires (care workers)	4.45	0.32	196	3.70	0.53	69	4.26	0.27	265
Exits (care workers)	3.36	0.23	196	2.96	0.41	69	3.26	0.20	265
Revenue per employee	337.5	4.83	196	350.4	10.11	69	340.9	4.44	265
Waitlist per capacity	1.54	0.11	187	1.67	0.24	66	1.58	0.10	253
Cases of restraint use	0.37	0.07	193	0.88	0.23	69	0.50	0.08	262
Cases of pressure ulcers	1.58	0.15	189	2.15	0.34	67	1.73	0.14	256
Cases of falls	2.58	0.30	188	2.97	0.63	67	2.68	0.27	255
Cases of falls at night	0.71	0.08	187	0.64	0.13	64	0.69	0.07	251
Cases of restraint use (dummy variable)	0.17	0.03	193	0.26	0.05	69	0.19	0.02	262
Cases of pressure ulcers (dummy variable)	0.59	0.04	189	0.70	0.06	67	0.62	0.03	256
Cases of falls (dummy variable)	0.70	0.03	188	0.73	0.05	67	0.71	0.03	255
Cases of falls at night (dummy variable)	0.40	0.04	187	0.36	0.06	64	0.39	0.03	251
Care worker (0yrs*) - regular, monthly (100 ¥)	1837	27.87	135	1769	42.86	45	1820	23.54	180
Care worker (0yrs) - regular, salary (100 ¥)	27550	430.8	135	26267	650.4	43	27240	364	178
Care worker (0yrs) - nonregular, hourly (100 ¥)	9.552	0.087	141	9.422	0.144	46	9.52	0.075	187
Care worker (5yrs*) - regular, monthly (100 ¥)	2125	32.95	144	2096	55.02	49	2118	28.22	193
Care worker (5yrs) - regular, salary (100 ¥)	32618	486.3	142	31889	825	47	32437	418.6	189
Care worker (5yrs) - nonregular, hourly (100 ¥)	10.39	0.11	138	10.16	0.188	44	10.33	0.095	182

*Care worker years of experience. Our survey asked nursing home managers to report the usual wages offered to care workers with 0 or 5 years of experience, hired as regular or nonregular employees.

Table 4. Summary statistics of control variables by robot adoption

	Adopted			Not adopted			Total			t-test
VARIABLES	mean	std.err	N	mean	std.err	N	mean	std.err	N	p-value
Log(capacity)	4.203	0.023	195	4.195	0.046	69	4.201	0.021	264	0.858
Technology										
Lift(standing assistance)	0.291	0.033	196	0.159	0.044	69	0.257	0.027	265	0.032
Wheelchair lift for cars	0.592	0.035	196	0.565	0.060	69	0.585	0.030	265	0.701
Adjustable bed	0.944	0.016	196	0.928	0.031	69	0.940	0.015	265	0.626
Wheelchair with built-in seat lift	0.071	0.018	196	0.043	0.025	69	0.064	0.015	265	0.417
Special bathtub (with side door)	0.832	0.027	196	0.826	0.046	69	0.830	0.023	265	0.916
Stretcher	0.898	0.022	196	0.942	0.028	69	0.909	0.018	265	0.274
Shower carry	0.709	0.033	196	0.609	0.059	69	0.683	0.029	265	0.124
Lifting device (only for lifting)	0.122	0.023	196	0.072	0.031	69	0.109	0.019	265	0.254
Wheelchair scales	0.939	0.017	196	0.913	0.034	69	0.932	0.015	265	0.467
Management practice										
Standardized protocols for care	2.397	0.042	194	2.323	0.073	65	2.378	0.036	259	0.381
Adjustable staffing	2.134	0.048	194	2.118	0.093	68	2.130	0.043	262	0.866
Problem resolution protocol	2.102	0.059	196	2.044	0.092	68	2.087	0.050	264	0.611
Performance tracking	1.985	0.081	194	1.940	0.134	67	1.973	0.069	261	0.781
Communication and feedback	1.908	0.075	195	1.868	0.127	68	1.897	0.064	263	0.785
Performance based promotion	2.421	0.048	195	2.433	0.077	67	2.424	0.040	262	0.894
Resident care level										
Log(care required level 1)	0.283	0.038	193	0.267	0.065	67	0.279	0.033	260	0.829
Log(care required level 2)	0.741	0.057	193	0.744	0.109	67	0.742	0.051	260	0.984
Log(care required level 3)	2.702	0.049	193	2.722	0.067	67	2.707	0.041	260	0.825
Log(care required level 4)	3.277	0.027	193	3.269	0.053	67	3.275	0.024	260	0.881
Log(care required level 5)	3.018	0.030	193	2.900	0.073	67	2.988	0.029	260	0.079
Log(dementia)	3.626	0.072	196	3.333	0.155	69	3.550	0.067	265	0.055
Covid cases										
Any Covid cases	0.230	0.030	196	0.246	0.052	69	0.234	0.026	265	0.778
Log(Covid cases)	0.287	0.047	196	0.309	0.083	69	0.293	0.041	265	0.812
Log(local covid cases)	0.741	0.073	196	0.726	0.125	69	0.737	0.063	265	0.92
Prefecture variables										
Log(population)	14.80	0.059	196	14.62	0.092	69	14.75	0.05	265	0.117
Log(population over 70)	13.27	0.053	196	13.10	0.083	69	13.23	0.045	265	0.109
Log(nursing home employees)	9.381	0.043	196	9.235	0.066	69	9.343	0.036	265	0.076
Hired-to-openings ratio	0.722	0.009	196	0.732	0.014	69	0.725	0.007	265	0.534
Log(minimum wage)	6.725	0.005	196	6.710	0.008	69	6.721	0.005	265	0.161

Table 5. Robots and staffing

	(1)	(2)	(3)	(4)	(5)
	Log(total employees)	Log(caregivers)			
		Total	Non-regular	Regular	Full-time equivalent
Panel A: Robot adoption					
Adopt robots	0.0309*	0.0466**	0.0698	0.0245	-0.0114
	(0.0165)	(0.0194)	(0.0669)	(0.0248)	(0.0352)
Nursing home and year FEs	Yes	Yes	Yes	Yes	Yes
Control variables	No	No	No	No	No
Observations	517	517	517	517	517
R-squared	0.047	0.036	0.019	0.007	0.004
Mean of dep. var.	4.010	3.627	1.951	3.421	3.501
Panel B: Robot adoption					
Adopt robots	0.0514***	0.0650***	0.137**	0.0199	-0.00387
	(0.0189)	(0.0226)	(0.0623)	(0.0270)	(0.0336)
Nursing home and year FEs	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	468	468	468	468	468
R-squared	0.219	0.209	0.195	0.152	0.205
Mean of dep. var.	4.015	3.634	1.952	3.428	3.510
Panel C: Number of robots in use					
Log(number of robots in use)	0.0144**	0.0221***	0.0312	0.0119	0.0132**
	(0.00626)	(0.00770)	(0.0286)	(0.0104)	(0.00577)
Nursing home and year FEs	Yes	Yes	Yes	Yes	Yes
Control variables	No	No	No	No	No
Observations	489	489	489	489	489
R-squared	0.061	0.059	0.020	0.011	0.021
Mean of dep. var.	4.012	3.627	1.955	3.419	3.504
Panel D: Number of robots in use					
Log(number of robots in use)	0.0240***	0.0296***	0.0510*	0.0136	0.0194***
	(0.00787)	(0.00941)	(0.0261)	(0.0112)	(0.00702)
Nursing home and year FEs	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	447	447	447	447	447
R-squared	0.242	0.226	0.200	0.166	0.225
Mean of dep. var.	4.017	3.636	1.958	3.428	3.515

Notes: Caregivers include care workers and nurses. Control variables include resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5; technology adoption controls for each non-robot technology used in the nursing homes; management practice controls for human resource management practices; and Covid-19 prevalence controls including cases and deaths. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Staffing results by robot type

	(1)	(2)	(3)	(4)	(5)
	Log(total employees)	Log(caregivers)			
		Total	Non-regular	Regular	Full-time equivalent
Panel A: Robot adoption by type					
Adopt monitoring robots	0.0536***	0.0584***	0.0798	0.0394	0.0299
	(0.0173)	(0.0215)	(0.0594)	(0.0244)	(0.0208)
Adopt mobility robots	0.00994	0.00920	-0.0226	-0.000838	0.00240
	(0.0172)	(0.0194)	(0.0749)	(0.0245)	(0.0257)
Adopt transfer robots	-0.0169	-0.0149	0.0410	-0.0101	-0.0261
	(0.0162)	(0.0209)	(0.0708)	(0.0231)	(0.0222)
Observations	468	468	468	468	468
R-squared	0.235	0.209	0.185	0.165	0.214
Mean of dep. var.	4.015	3.634	1.952	3.428	3.510
Panel B: Number of robots in use by type					
Log(number of monitoring robots in use)	0.0249***	0.0288***	0.0485*	0.0190*	0.0199***
	(0.00830)	(0.00999)	(0.0264)	(0.0114)	(0.00753)
Log(number of mobility robots in use)	-0.000862	-0.00225	-0.0437	-0.0102	0.00189
	(0.0108)	(0.0129)	(0.0399)	(0.0148)	(0.0120)
Log(number of transfer robots in use)	-0.00121	0.00157	0.0425	-0.00251	-0.00503
	(0.0133)	(0.0146)	(0.0492)	(0.0208)	(0.0143)
Observations	447	447	447	447	447
R-squared	0.246	0.222	0.202	0.176	0.228
Mean of dep. var.	4.017	3.636	1.958	3.428	3.515

Notes: All regressions include nursing home and year fixed effects, and control variables. Control variables include resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5; technology adoption controls for each non-robot technology used in the nursing homes; management practice controls for human resource management practices; and Covid-19 prevalence controls including cases and deaths. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Robots and care worker turnover

VARIABLES	(1) Hire rate	(2) Hire rate - Regular	(3) Hire rate - Non-regular	(4) Exit rate	(5) Exit rate - Regular	(6) Exit rate - Non-regular
Panel A: Robot adoption						
Adopt robots	-0.0141	0.00108	-0.0121	-0.0387	-0.0102	-0.0279**
	(0.0266)	(0.0193)	(0.0139)	(0.0241)	(0.0149)	(0.0139)
Observations	468	468	468	468	468	468
R-squared	0.206	0.215	0.220	0.222	0.173	0.221
Mean of dep. var.	0.141	0.0899	0.0505	0.119	0.0794	0.0397
Panel B: Number of robots in use						
Log(number of robots	-0.0108	-0.00302	-0.00720	-0.0154	-0.00711	-0.00818
in use)	(0.0115)	(0.00779)	(0.00605)	(0.00954)	(0.00625)	(0.00518)
Observations	447	447	447	447	447	447
R-squared	0.207	0.227	0.227	0.232	0.186	0.255
Mean of dep. var.	0.142	0.0904	0.0507	0.121	0.0802	0.0405
Panel C: Robot adoption by type						
Adopt monitoring	-0.0191	-0.0155	-0.00203	-0.0206	-0.00676	-0.0130
robots	(0.0239)	(0.0161)	(0.0138)	(0.0193)	(0.0125)	(0.0111)
Adopt mobility robots	-0.0413	-0.0147	-0.0296	-0.0527*	-0.0343	-0.0195
	(0.0479)	(0.0333)	(0.0209)	(0.0310)	(0.0212)	(0.0152)
Adopt transfer robots	0.0298	0.0171	0.0102	0.0335	0.0180	0.0164
	(0.0259)	(0.0166)	(0.0163)	(0.0251)	(0.0173)	(0.0137)
Observations	468	468	468	468	468	468
R-squared	0.217	0.223	0.230	0.237	0.191	0.218
Mean of dep. var.	0.141	0.0899	0.0505	0.119	0.0794	0.0397
Panel D: Number of robots in use by type						
Log(number of	-0.00922	-0.00502	-0.00348	-0.00949	-0.00226	-0.00706
monitoring robots in use)	(0.0108)	(0.00698)	(0.00627)	(0.00948)	(0.00598)	(0.00535)
Log(number of	-0.0200	-0.00631	-0.0145	-0.0398***	-0.0304***	-0.00949
mobility robots in use)	(0.0223)	(0.0138)	(0.0120)	(0.0143)	(0.0108)	(0.00740)
Log(number of transfer	0.0175	0.0151	0.00259	0.0240	0.0111	0.0128*
robots in use)	(0.0154)	(0.00944)	(0.00946)	(0.0168)	(0.0133)	(0.00731)
Observations	447	447	447	447	447	447
R-squared	0.214	0.235	0.231	0.265	0.223	0.269
Mean of dep. var.	0.142	0.0904	0.0507	0.121	0.0802	0.0405

Notes: All regressions include nursing home and year fixed effects, and control variables. Control variables include resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5; technology adoption controls for each non-robot technology used in the nursing homes; management practice controls for human resource management practices; and Covid-19 prevalence controls including cases and deaths. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Robot adoption and task automation

VARIABLES	(1) Task automation index	(2) Monitoring task automation index	(3) Mobility task automation index	(4) Transfer task automation index
Panel A: Robot adoption				
Adopt robots	0.138***	0.212***	0.0741*	0.0860*
	(0.0350)	(0.0578)	(0.0405)	(0.0455)
Observations	452	452	450	449
R-squared	0.156	0.148	0.097	0.200
Mean of dep. var.	1.449	1.659	1.234	1.333
Panel B: Number of robots in use				
Log(number of robots in use)	0.0637***	0.106***	0.0288**	0.0358*
	(0.0161)	(0.0241)	(0.0142)	(0.0202)
Observations	432	432	430	429
R-squared	0.177	0.183	0.125	0.223
Mean of dep. var.	1.455	1.667	1.240	1.337
Panel C: Robot adoption by type				
Adopt monitoring robots	0.129***	0.218***	0.0160	0.107**
	(0.0329)	(0.0513)	(0.0301)	(0.0459)
Adopt mobility robots	0.0885*	0.0954	0.154**	0.0166
	(0.0489)	(0.0622)	(0.0625)	(0.0633)
Adopt transfer robots	0.0129	-0.0130	0.0194	0.0400
	(0.0450)	(0.0660)	(0.0405)	(0.0685)
Observations	452	452	450	449
R-squared	0.186	0.180	0.134	0.217
Mean of dep. var.	1.449	1.659	1.234	1.333
Panel D: Number of robots in use by type				
Log(number of monitoring robots in use)	0.0617***	0.109***	0.0163	0.0370
	(0.0165)	(0.0236)	(0.0128)	(0.0233)
Log(number of mobility robots in use)	0.0389	0.0413	0.0542*	0.0211
	(0.0242)	(0.0276)	(0.0311)	(0.0358)
Log(number of transfer robots in use)	0.00584	-0.0251	0.0231	0.0313
	(0.0334)	(0.0459)	(0.0300)	(0.0477)
Observations	432	432	430	429
R-squared	0.194	0.205	0.138	0.232
Mean of dep. var.	1.455	1.667	1.240	1.337

Notes: All regressions include nursing home and year fixed effects, and control variables. Control variables include resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5; technology adoption controls for each non-robot technology used in the nursing homes; management practice controls for human resource management practices; and Covid-19 prevalence controls including cases and deaths. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9. Task automation and care staffing

	(1)	(2)	(3)	(4)	(5)
	Log(total employees)	Log(caregivers)			
		Total	Non-regular	Regular	Full-time equivalent
Panel A. Average task automation					
Task automation index	0.0494**	0.0716***	0.0833	0.0434	0.0592**
	(0.0204)	(0.0238)	(0.0785)	(0.0289)	(0.0283)
Observations	461	461	461	461	461
R-squared	0.210	0.184	0.143	0.125	0.207
Mean of dep. var.	4.016	3.636	1.963	3.427	3.512
Panel B. Task automation by task groups					
Monitoring task automation index	0.0306*	0.0357*	-0.00300	0.0261	0.0544**
	(0.0176)	(0.0196)	(0.0783)	(0.0277)	(0.0254)
Mobility task automation index	0.0302	0.0301	0.0362	0.0116	-0.0144
	(0.0207)	(0.0262)	(0.0686)	(0.0295)	(0.0356)
Transfer task automation index	-0.0147	0.0117	0.0653	0.00576	-0.00942
	(0.0232)	(0.0275)	(0.0944)	(0.0315)	(0.0427)
Observations	458	458	458	458	458
R-squared	0.216	0.186	0.148	0.126	0.214
Mean of dep. var.	4.017	3.637	1.966	3.427	3.380

Notes: All regressions include nursing home and year fixed effects, and control variables. Control variables include resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5; technology adoption controls for each non-robot technology used in the nursing homes; management practice controls for human resource management practices; and Covid-19 prevalence controls including cases and deaths. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10. Robots and nursing home productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Quantity of care			Quality of care			
VARIABLES	Log(number of residents)	Log(revenue)	Waitlist/ capacity	Log(restraint use)	Log(ulcer cases)	Log(falls)	Log(falls at night)
Panel A: Robot adoption							
Adopt robots	0.0215**	0.0196**	0.312***	-0.130**	-0.258**	0.0437	-0.0711
	(0.00895)	(0.00919)	(0.117)	(0.0635)	(0.108)	(0.139)	(0.0862)
Observations	468	468	444	466	457	458	453
R-squared	0.343	0.331	0.138	0.119	0.177	0.108	0.125
Mean of dep. var.	4.132	9.835	1.729	0.220	0.691	0.948	0.413
Panel B: Number of robots in use							
Log(number of robots in use)	0.00844**	0.00791**	0.101**	-0.0272	-0.0462	0.0654	0.00527
	(0.00369)	(0.00389)	(0.0422)	(0.0218)	(0.0389)	(0.0546)	(0.0313)
Observations	447	447	423	445	438	437	432
R-squared	0.367	0.351	0.216	0.120	0.179	0.113	0.136
Mean of dep. var.	4.134	9.836	1.724	0.205	0.699	0.953	0.423
Panel C: Robot adoption by type							
Adopt monitoring robots	0.0235***	0.0213**	0.0217	-0.179***	-0.0948	-0.0822	-0.122*
	(0.00894)	(0.00900)	(0.182)	(0.0562)	(0.0942)	(0.114)	(0.0702)
Adopt mobility robots	0.00470	0.00417	0.130	-0.00412	0.162	0.503***	0.275***
	(0.00928)	(0.00966)	(0.106)	(0.0620)	(0.117)	(0.173)	(0.0996)
Adopt transfer robots	0.0152*	0.0169**	0.0969	-7.34e-05	-0.0979	-0.182	0.0841
	(0.00842)	(0.00852)	(0.128)	(0.0449)	(0.109)	(0.123)	(0.0789)
Observations	468	468	444	466	457	458	453
R-squared	0.358	0.346	0.122	0.153	0.165	0.161	0.166
Mean of dep. var.	4.132	9.835	1.729	0.220	0.691	0.948	0.413
Panel D: Number of robots in use by type							
Log(number of monitoring robots in use)	0.00958**	0.00939**	0.0978**	-0.0264	-0.0486	0.0254	-0.0372
	(0.00370)	(0.00385)	(0.0466)	(0.0204)	(0.0394)	(0.0495)	(0.0316)
Log(number of mobility robots in use)	-0.00244	-0.00458	8.37e-06	-0.0199	0.0668	0.292***	0.154**
	(0.00495)	(0.00525)	(0.0586)	(0.0269)	(0.0579)	(0.0984)	(0.0775)
Log(number of transfer robots in use)	0.00793*	0.00913*	-0.0121	0.0167	-0.0511	-0.120	0.0587
	(0.00479)	(0.00489)	(0.0525)	(0.0289)	(0.0630)	(0.0774)	(0.0581)
Observations	447	447	423	445	438	437	432
R-squared	0.375	0.361	0.215	0.124	0.184	0.162	0.174
Mean of dep. var.	4.134	9.836	1.724	0.205	0.699	0.953	0.423

Notes: All regressions include nursing home and year fixed effects, and control variables. Control variables include resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5; technology adoption controls for each non-robot technology used in the nursing homes; management practice controls for human resource management practices; and Covid-19 prevalence controls including cases and deaths. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11. Staffing results by worker type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(care workers)				log(nurses)			
	Total	Non-regular	Regular	Full-time equivalent	Total	Non-regular	Regular	Full-time equivalent
Panel A: Robot adoption								
Adopt robots	0.0586**	0.0855	0.0219	-0.0278	0.102**	0.143	-0.00176	0.0809**
	(0.0229)	(0.0692)	(0.0267)	(0.0472)	(0.0461)	(0.0881)	(0.0452)	(0.0348)
Observations	468	468	468	468	468	468	468	468
R-squared	0.214	0.180	0.166	0.208	0.132	0.137	0.116	0.150
Mean of dep. var.	3.489	1.755	3.306	3.376	1.565	0.717	1.472	1.371
Panel B: Robot adoption by type								
Adopt monitoring robots	0.0584***	0.0458	0.0433*	0.0281	0.0596	0.0840	0.0163	0.0491
	(0.0224)	(0.0703)	(0.0241)	(0.0242)	(0.0457)	(0.0816)	(0.0430)	(0.0360)
Adopt mobility robots	0.00539	-0.0453	0.000920	0.00361	0.0155	0.00478	0.00212	0.00759
	(0.0212)	(0.0828)	(0.0262)	(0.0306)	(0.0415)	(0.0793)	(0.0432)	(0.0401)
Adopt transfer robots	-0.0176	0.0349	-0.0120	-0.0338	0.00628	0.0150	-0.00486	0.0167
	(0.0215)	(0.0753)	(0.0232)	(0.0255)	(0.0400)	(0.0698)	(0.0405)	(0.0337)
Observations	468	468	468	468	468	468	468	468
R-squared	0.222	0.177	0.182	0.211	0.116	0.128	0.117	0.138
Mean of dep. var.	3.489	1.755	3.306	3.376	1.565	0.717	1.472	1.371
Panel C: Number of robots in use								
Log(number of robots in use)	0.0269***	0.0342	0.0146	0.0170**	0.0429**	0.0556*	0.00662	0.0400***
	(0.00923)	(0.0272)	(0.0110)	(0.00734)	(0.0175)	(0.0299)	(0.0175)	(0.0122)
Observations	447	447	447	447	447	447	447	447
R-squared	0.232	0.202	0.177	0.207	0.178	0.162	0.132	0.244
Mean of dep. var.	3.491	1.760	3.306	3.383	1.567	0.725	1.469	1.372
Panel D: Number of robots in use by type								
Log(number of monitoring robots in use)	0.0281***	0.0310	0.0199*	0.0196**	0.0313*	0.0403	0.0153	0.0259**
	(0.01000)	(0.0289)	(0.0113)	(0.00803)	(0.0182)	(0.0310)	(0.0176)	(0.0124)
Log(number of mobility robots in use)	-0.00559	-0.0352	-0.00923	-0.00165	0.0168	0.00592	-0.0114	0.0263*
	(0.0132)	(0.0413)	(0.0151)	(0.0131)	(0.0235)	(0.0590)	(0.0291)	(0.0151)
Log(number of transfer robots in use)	-0.00208	0.0364	-0.00383	-0.00879	0.0228	0.0223	-0.00466	0.0256
	(0.0158)	(0.0493)	(0.0213)	(0.0150)	(0.0230)	(0.0397)	(0.0275)	(0.0201)
Observations	447	447	447	447	447	447	447	447
R-squared	0.234	0.203	0.188	0.214	0.167	0.155	0.136	0.232
Mean of dep. var.	3.491	1.760	3.306	3.383	1.567	0.725	1.469	1.372

Notes: All regressions include nursing home and year fixed effects, and control variables. Control variables include resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5; technology adoption controls for each non-robot technology used in the nursing homes; management practices control for human resource management practices; and Covid-19 prevalence controls including cases and deaths. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12. Robots and care worker earnings by experience

	(1)	(2)	(3)	(4)
	Log earnings of care workers with no experience		Log earnings of care workers with 5 years of experience	
VARIABLES	Regular (monthly+bonus)	Non-regular (hourly)	Regular (monthly+bonus)	Non-regular (hourly)
Panel A: Robot adoption				
Adopt robots	0.0250	-0.0780	0.000324	0.00144
	(0.0266)	(0.0858)	(0.0274)	(0.0129)
Observations	345	360	372	358
R-squared	0.255	0.312	0.680	0.362
Mean of dep. var.	14.74	6.818	14.86	6.916
Panel B: Number of robots in use				
Log(number of robots in use)	0.0197*	-0.0665	-0.000818	-0.00992*
	(0.0111)	(0.0533)	(0.0131)	(0.00525)
Observations	332	345	356	345
R-squared	0.311	0.334	0.687	0.379
Mean of dep. var.	14.74	6.818	14.87	6.918
Panel C: Robot adoption by type				
Adopt monitoring robots	0.0287	-0.0367	0.00705	-0.0162
	(0.0293)	(0.0632)	(0.0278)	(0.0127)
Adopt mobility robots	-0.0138	0.0303	-0.0660*	-0.0173
	(0.0365)	(0.0869)	(0.0362)	(0.0168)
Adopt transfer robots	0.0366	-0.176	0.0459	0.0101
	(0.0352)	(0.143)	(0.0397)	(0.0133)
Observations	345	360	372	358
R-squared	0.267	0.322	0.689	0.377
Mean of dep. var.	14.74	6.818	14.86	6.916
Panel D: Number of robots in use by type				
Log(number of monitoring robots in use)	0.0220**	-0.0546	0.00858	-0.0137**
	(0.0107)	(0.0425)	(0.0137)	(0.00535)
Log(number of mobility robots in use)	-0.0189	-0.0218	-0.0503**	0.00165
	(0.0247)	(0.0502)	(0.0238)	(0.00861)
Log(number of transfer robots in use)	0.0272	-0.0951	0.0116	-0.00118
	(0.0213)	(0.0821)	(0.0196)	(0.00732)
Observations	332	345	356	345
R-squared	0.329	0.341	0.699	0.398
Mean of dep. var.	14.74	6.818	14.87	6.918

Notes: All regressions include nursing home and year fixed effects, and control variables. Control variables include resident case-mix controls for the log number of residents with care levels 1-3, 4, and 5; technology adoption controls for each non-robot technology used in the nursing homes; management practices control for human resource management practices; and Covid-19 prevalence controls including cases and deaths. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.