Loneliness among workers in Japan during the pandemic

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Abstract

Inexpensive wages and a high-stress environment may lead to a prevalence of loneliness among workers in Japan. In contrast, the changing working conditions and socioeconomic factors during the pandemic may contribute to post-pandemic loneliness. As a result, we studied associations between loneliness and various types of work and employment status among workers in Japan while also considering the timeline of the pandemic. Utilising Hiroshima University's annual panel survey, we also tracked workers' movement in the labour market from February 2020, before the reclassification of the spread of COVID-19 from an epidemic to a pandemic, until February 2022, almost two years after the pandemic. We found heterogeneous associations between types of employment and the likelihood of feeling lonely. Full-time private and freelancer workers are among the most susceptible group to developing long-term loneliness. Furthermore, we found various associations between labour movements and workers' loneliness. The different motivations underlying the movements in the labour market may also serve as the causes of varying loneliness outcomes. As a result, we argue against universal countermeasure policies and suggest that policymakers consider the underlying differences when designing curbing measures in the future.

1. Introduction

The COVID-19 pandemic and its countermeasures are the catalysts for the increasing loneliness issues worldwide [1]. In Japan, longitude studies found that people of different ages and gender became lonelier during the pandemic at different magnitudes [2-4]. Recent cross-sectional studies also found that occupation and employment status led to heterogeneous results among workers in Japan during the pandemic [5-10]. Nevertheless, these cross-sectional studies disregarded the prevalence of loneliness before the pandemic, unlike previous studies on age and gender. Kadoya et al. [4] found that loneliness widely infected the Japanese population before the COVID-19 pandemic. Long working hours under a high-stress environment with little compensation may contribute to long-term loneliness among workers [11-14], whereas changing working conditions and socioeconomic factors during the pandemic could contribute to post-pandemic loneliness. Focusing on cross-sectional data would prevent previous studies from observing the changing working conditions and socioeconomic conditions likely to impact workers' loneliness during the pandemic. Since no longitude study observed these changes, we expanded the loneliness conditions into long-term and post-pandemic to further study the issue among workers.

The intensified pandemic situation and the reduction in social contact measures led several studies to study loneliness issues among workers in Japan [5-10,15]. In general, job characteristics and changes in employment status and environment are correlated with loneliness levels and mental health problems. Studies found that increased work stress and increased workload during the pandemic are associated with loneliness. For example, healthcare workers were lonelier than the general population [8]. Meanwhile, non-healthcare workers with a higher variance in workload were lonelier than their counterparts [5]. Studies also found positive associations between distance work and mental well-being indicators such as stress level and loneliness level [9,10]. The lack of colleagues' support for distance workers may contribute to such relationships [5,9]. In addition to a lack of social contact with others, workers who spent less time with their families during the pandemic were lonelier than others [6]. Furthermore, being on a furlough positively correlates with lower mental well-being [10].

Despite the attention to loneliness during the pandemic, studies on loneliness among workers in Japan failed to incorporate the prevalence of loneliness before the pandemic and make a distinction between long-term loneliness and post-pandemic loneliness. The findings might misguide the public that returning to normalcy before the pandemic will resolve loneliness issues among workers in Japan. Furthermore, these studies did not distinguish workers based on their type of work and employment movement status within the same analysis. As a result, we utilised a panel data survey and studied loneliness among workers in Japan, taking the COVID-19 timeline and different employment variables. We distinguish between long-term and post-pandemic loneliness and observe which group of workers are more prone to these loneliness issues. Our study contributes to the public and academic world in several ways. First, our study is among the first in Japan to include loneliness before the announcement of the pandemic in March 2020 and separate long-term loneliness from post-pandemic loneliness. Second, since we utilised a panel data survey, our study is among the first in Japan to include different types of workers and track workers' movement throughout the pandemic. Lastly, our ability to observe long-term loneliness among workers allows our study to provide valuable guidelines to policymakers on addressing the loneliness issues among workers in Japan.

The study consists of five sections. We begin with an introduction in Section 1, followed by data and methods in Section 2. Later, we provided the results and discussed the results in Section 3 and Section 4, respectively. Finally, we conclude our study in Section 5.

2. Data and Methods

2.1 Data

Our study utilised a Hiroshima University funded survey called "Household Behavioral and Financial Survey". Hiroshima University's Hiroshima Institute of Health Economics Research (HiHER) conducted three waves of surveys from 2020 to 2022 with the help of Nikkei Research. This prominent Japanese research company has broad databases with a socioeconomic status comparable to the Japanese population. Corresponding to the pandemic time frame, HiHER conducted the first survey on 20th-25th February 2020, before the declaration of the COVID-19 pandemic in March 2020. Then, the institute conducted the second survey on 19th-26th February 2021 and the third survey on 18th-28th February 2022. HiHER collected the respondents' socioeconomic status, preference, and well-being following the random sampling procedure while maintaining the representativeness of the data. The complete database consists of 4,281 responses from respondents who participated in the survey every year. Due to the missing essential information on socioeconomic status like financial status, we dropped some observations and used 2,630 observations in this study.

Regarding ethical scrutiny, HiHER does not collect any sensitive individual information, which may lead to an identification of our survey respondents. As a result, Hiroshima University does not request us to apply for ethical scrutiny. However, HiHER informed the respondents about the purpose of the survey, obtained their consent, and allowed them to omit any questions they felt uncomfortable with.

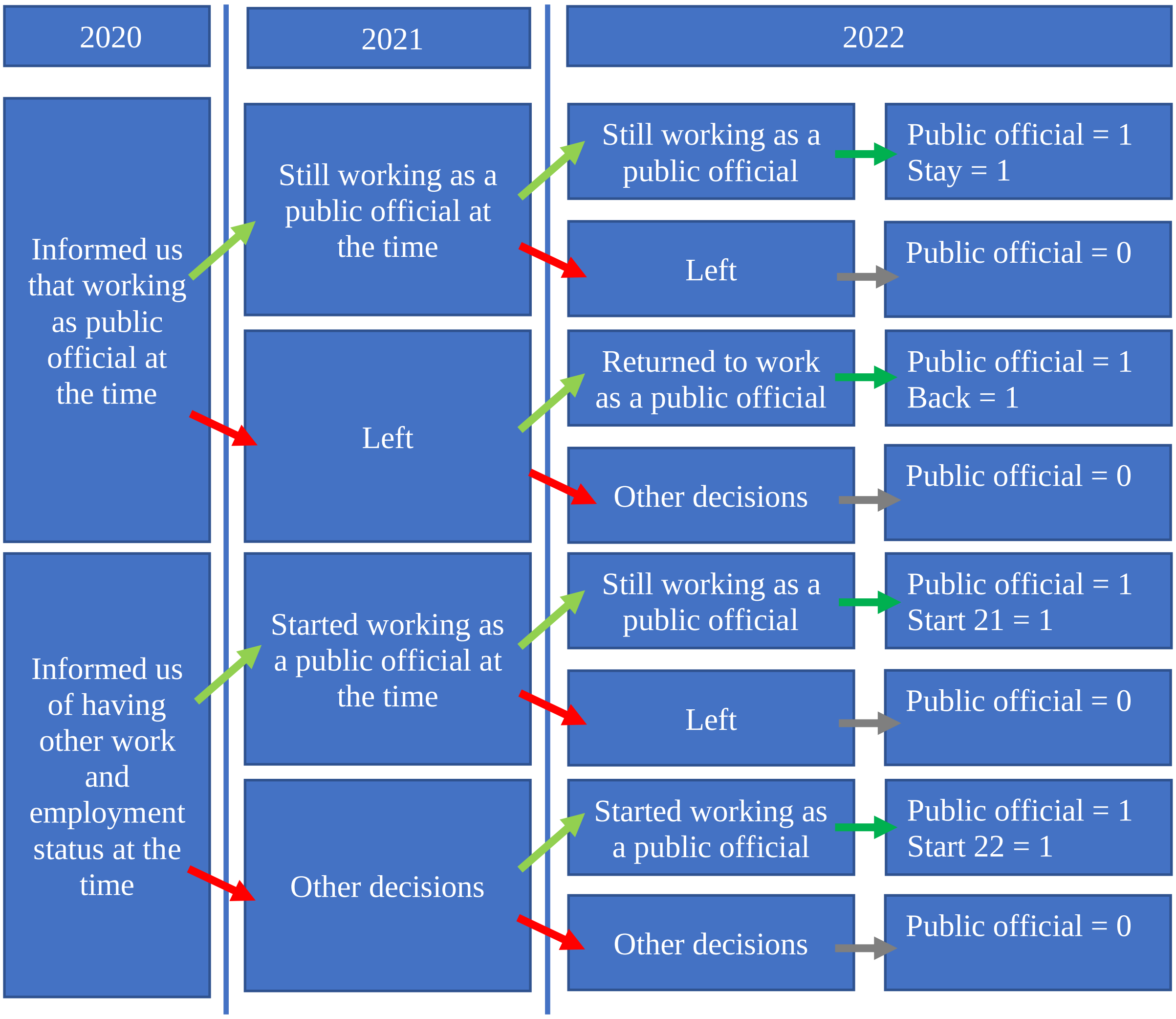
2.2 Variable definitions

When it comes to loneliness among workers, here are our questions. Do people feel lonely equally regardless of their work and employment status? If not, who is currently lonelier? Moreover, which group of workers is more prone to long-term and post-pandemic loneliness? We utilised the UCLA methodology [16] to answer these questions. Within the survey, the respondents were asked three UCLA loneliness-related questions: "How often do you feel a lack of companionship", "How often do you feel left out", and "How often do you feel isolated from others". These responses also were provided: "Hardly ever or never", "Some of the time", and "Often". Then, we assigned the score corresponding to their response. If the respondent answered "Hardly ever or never", we encrypted 0. If the respondent answered "Some of the time", we encrypted 1. If the respondent answered "Often", we encrypted 2.

Besides creating a non-dichotomous variable, we followed Khan and Kadoya [2], Khan et al. [3], and Kadoya et al. [4,17] and created a similar loneliness variable. If the respondents answered "Some of the time" or "Often" to any loneliness-related questions, we categorised them as feeling lonely (loneliness = 1). Otherwise, we classified them as not feeling lonely (loneliness = 0). In addition to measuring general loneliness, we are interested in long-term and post-pandemic loneliness. Since our data collection timeline coincides with the pandemic timeline, we can observe those who were lonely before the declaration of the pandemic in March 2020 and those who were lonely afterwards. Following Kadoya et al. [4], we generated variables corresponding to this timeline. If our respondents have suffered from loneliness since before the declaration of the pandemic and continue to suffer till 2022, we categorised them as people who suffered from long-term loneliness (long-term loneliness = 1). Otherwise, we encrypted long-term loneliness as 0. Meanwhile, if our respondents started to feel lonely after the first wave of data collection in 2020, we categorised these people as people who suffered from post-pandemic loneliness (post-pandemic loneliness = 1). Otherwise, we encrypted post-pandemic loneliness as 0.

Since our study focuses on loneliness among workers, our explanatory variables are work and employment status. We utilised the survey question, "Do you currently work? If so, what type of job do you do? In case you don't work, please pick "I don't work." (Check only one option)", which provides twelve options: "Full-time employee (Private sector)", "(term) Contract employee", "Public official (Full-time)", "Specialist (MD/lawyer/Account etc.)", "Self-employed", "Freelance worker", "House wife/husband", "Part-time worker (student)", "Part-time worker (non-student)", "Others (specify:)", "I don't work", and "I don't want to answer". Then, we create five dummy variables corresponding to these options. Public job, Private job, Freelance job, Part-time job, and No employment. It is straightforward that if our respondents picked "Public official (Full-time)" or "Full-time employee (Private sector)', we encrypted Public job or Private job as 1, respectively. Otherwise, we encrypted them as 0. On the other hand, we combined some respondents with different work statuses due to low statistical power. We categorised respondents who are "Specialist (MD/lawyer/Account etc.)", "Self-employed", and "Freelance worker" as freelance workers (freelance job = 1). Otherwise, we encrypted it as 0. We also categorised respondents who work part-time regardless of their student enrolment status (part-time job = 1). Otherwise, the part-time job is encrypted as 0. Finally, those who selected "House wife/husband", "Others (specify:)", and "I don't work" are categorised as those who do not have stable employment (no employment = 1). Besides creating work and employment status variables, we also utilised the nature of the panel survey and tracked the employment movement of our respondents. We found that there are four possible movements for each work and employment status variable, which the example is shown in Figure 1. Thereby, we create four variables for each work status dummies: "Stay", "Start 22", "Start 21", and "Back". If respondents have stayed on the same career path since 2020, we encrypted stay as 1. Otherwise, we encrypted stay as 0. Meanwhile, if respondents have recently started their current career path in 2022, we encrypted start 22 as 1. Otherwise, we encrypted start 22 as 0. If respondents recently returned to their initial work status in 2022 after temporarily changing their work status in 2021, we encrypted back as 1. Otherwise, we encrypted back as 0. Lastly, if respondents have started their career path in 2021, we encrypted start 21 as 1. Otherwise, we encrypted start 21 as 0.

Figure 1. Example movement of workers who are public officials in 2022



Since socioeconomic studies like Kadoya et al. [4], Khan et al. [3], Yuktadatta et al. [18], Kadoya et al. [19], and Kadoya et al. [20] used the same database as ours. We followed these studies in creating similar explanatory variables. In this study, we included demographic, household, financial, behaviour, future anxiety, physical, mental health, and perception variables, which are explained in detail in Table 1.

Table 1. Variable definitions.

Variables	**Definition**
	Dependent variables
Loneliness	Binary variable: 1 = having feelings of loneliness some of the time or often, and 0 = otherwise.
Long-term loneliness	Binary variable: 1=feeling lonely in all three years (2020, 2021, 2022), and 0=otherwise
Post-pandemic loneliness	Binary variable: 1=not feeling lonely in 2020, but becoming lonely in 2021 and remaining in that condition in 2022, and 0=otherwise
	Interested explanatory variables
Public job	Binary variable: 1 = Public official and 0 = Otherwise
Private job	Binary variable: 1 = Private employee and 0 = Otherwise
Freelance job	Binary variable: 1 = Freelancer or Contract worker and 0 = Otherwise

Variables	Definition
Part-time job	Binary variable: 1 = Part-time worker and 0 = Otherwise
No employment	Binary variable: 1 = No employment and 0 = Otherwise
Stay	Binary variable: 1 = Stay in their job since 2020 and 0 = Otherwise
Start 22	Binary variable: 1 = Start working at their current job in 2022 and 0 = Otherwise
Start 21	Binary variable: 1 = Start working at their current job in 2021 and 0 = Otherwise
Back	Binary variable: 1 = Left their job earlier in 2021 but return to the job in 2022 and 0 = Otherwise
Control variables	
• Demographic characteristics	
Male*	Binary variable: 1 = Male and 0 = Female
Age*	Continuous variable: Respondent's age in 2021
Living in rural	Binary variable: 1 = Living in rural areas (not Tokyo special wards or government-designated city areas) and 0 = Otherwise
Education	Discrete variable: Years of education
• Household characteristics	
Spouse	Binary variable: 1 = Currently have a spouse or partner and 0 = otherwise
Children	Binary variable: 1 = Having a child/children and 0 = otherwise
Living alone	Binary variable: 1 = Living alone and 0 = Otherwise
• Financial characteristics	
Household income	Continuous variable: Annual earned income before taxes and with bonuses of the entire household in 2020 (unit: JPY)
Log of HH income	Log of household income
Household assets	Continuous variable: Balance of financial assets (savings, stocks, bonds, insurance, etc.) of entire household (unit: JPY)
Log of HH assets	Log of household assets
Financial literacy*	Continuous variable: Average correct answers to three financial literacy questions
• Behaviour and future anxiety characteristics	
Smartphone usage	Continuous variable: The number of minutes that respondents spend using their smartphones
Future anxiety	Ordinal variable: 1 = It does not hold true at all for you; 2 = It is not so true for you; 3 = Neither true nor not true; 4 = It is rather true for you; 5 = It is particularly true for you for the statement "I have anxieties about 'life after 65 years of age' (For those who were already aged 65 years or above, 'life in the future')."
• Physical health characteristics	
Subjective health status	Ordinal variable: 1 = It does not hold true at all for you; 2 = It is not so true for you; 3 = Neither true nor not true; 4 = It is rather true for you; 5 = It is particularly true for you for the statement "I am now healthy and was generally healthy in the last one year."
• Mental health characteristics	
Depression	Ordinal variable: 1 = It does not hold true at all for you; 2 = It is not so true for you; 3 = Neither true nor not true; 4 = It is rather true for you; 5 = It is particularly true for you, for the statement, "I often feel depressed or felt depressed in the last one year."
• Perception characteristics	

Variables	Definition
Financial satisfaction	Ordinal variable: 1 = Completely disagree; 2 = Disagree; 3 = Neither agree nor disagree; 4 = Agree; 5 = Completely agree, for the statement, “Since the future is uncertain, it is a waste to think about it.” I am happy with my financial status.”
Myopic view of the future	Ordinal variable: 1 = Completely disagree; 2 = Disagree; 3 = Neither agree nor disagree; 4 = Agree; 5 = Completely agree with the statement “As the future is uncertain, it is a waste to think about it.”

2.3 Descriptive statistics

Our descriptive statistics (Table 2) revealed that 65% of the respondents are lonely; 52% suffer from long-term loneliness and around 7% suffer from post-pandemic loneliness. The average loneliness score is about 1.9 out of 6. For employment variables, we found that approximately 72% of our respondents have a job. 5.78% work in the public sector, while 38.10% work full-time in a private company. 19.39% are freelancers, contract workers, or specialists. 9.05% are part-time workers. Regarding employment movement, Table 2 also shows that each type of employment has a different proportion of movements. We found that most respondents (76.47% - 89.52%) have maintained their work status for the last three years, where part-time workers have the lowest staying ratio and full-time private workers have the highest rate. Meanwhile, the public job has the highest returning ratio of 6.58% and the highest starting ratio of 7.24%. We also found that full-time private employees have the lowest percentage of people who started working as full-time private employees (4.09%) or returned to their position (1.90%).

Table 2. Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max
Dependent variables				
Loneliness level	1.8951	1.9162	0.0000	6.0000
Loneliness	0.6513	0.4766	0.0000	1.0000
Long-term loneliness	0.5213	0.4996	0.0000	1.0000
Post-pandemic loneliness	0.0681	0.2519	0.0000	1.0000
Main Explanatory variables				
Private job	0.3810	0.4857	0.0000	1.0000
Stay	0.3411	0.4742	0.0000	1.0000
Start 22	0.0156	0.1239	0.0000	1.0000
Start 21	0.0171	0.1297	0.0000	1.0000
Back	0.0072	0.0847	0.0000	1.0000
Public job	0.0578	0.2334	0.0000	1.0000
Stay	0.0471	0.2120	0.0000	1.0000
Start 22	0.0042	0.0645	0.0000	1.0000
Start 21	0.0027	0.0515	0.0000	1.0000
Back	0.0038	0.0616	0.0000	1.0000
Freelance job	0.1939	0.3954	0.0000	1.0000
Stay	0.1589	0.3657	0.0000	1.0000
Start 22	0.0133	0.1146	0.0000	1.0000
Start 21	0.0167	0.1283	0.0000	1.0000
Back	0.0049	0.0701	0.0000	1.0000
Part-time job	0.0905	0.2869	0.0000	1.0000
Stay	0.0692	0.2538	0.0000	1.0000

Variable	Mean	Std. Dev.	Min	Max
Start 22	0.0065	0.0802	0.0000	1.0000
Start 21	0.0125	0.1113	0.0000	1.0000
Back	0.0023	0.0477	0.0000	1.0000
No employment	0.2768	0.4475	0.0000	1.0000
Stay	0.2373	0.4255	0.0000	1.0000
Start 22	0.0175	0.1311	0.0000	1.0000
Start 21	0.0179	0.1325	0.0000	1.0000
Back	0.0042	0.0645	0.0000	1.0000
Other Explanatory variables				
Male	0.6970	0.4597	0.0000	1.0000
Age	53.8266	12.7165	22.0000	87.0000
Spouse	0.6707	0.4700	0.0000	1.0000
Children	0.5916	0.4916	0.0000	1.0000
Living alone	0.2023	0.4018	0.0000	1.0000
Living in rural	0.5726	0.4948	0.0000	1.0000
Education	15.0177	2.0961	9.0000	21.0000
Household income*	6511217	4262293	500000	21000000
Log of HH income	15.4432	0.7806	13.1224	16.8600
Household assets*	24100000	31900000	1250000	125000000
Log of HH assets	16.0954	1.4524	14.0387	18.6438
Financial literacy	0.7099	0.3305	0.0000	1.0000
Smartphone usage	121.2319	132.3550	0.0000	1380.0000
Subjective health status	3.2738	1.1310	1.0000	5.0000
Future anxiety	3.7810	1.1488	1.0000	5.0000
Financial satisfaction	2.8510	1.0959	1.0000	5.0000
Depression	2.8871	1.2445	1.0000	5.0000
Myopic view of the future	2.6882	1.0048	1.0000	5.0000
Observations		2630		

In addition to Table 2, we compare the percentages of lonely people in the pre-pandemic (2020) to those in the post-pandemic (2022). Overall, our t-test reported that the percentage of lonely people between those two periods is relatively similar at a 90% significant level. We found a substantial decrease in lonely people among private full-time workers and people without employment at a 99% and a 95% significant level, respectively. After dividing people into the four distinct movement groups, we found a substantial decrease in the proportion of those who have worked as private full-time workers since 2020 at a 99% significant level. We also saw a considerable decline in the proportion of lonely people living without employment since 2020 at a 95% significant level. Finally, we found a significant decrease in the proportion of those who started living without employment in 2022 at a 90% significant level.

Table 3. Comparison of the percentage of lonely people during the pre-pandemic (2020 and the post-pandemic (2022).

Employment variable	Pre-pandemic	Post-pandemic	Paired t-test
Private	707 70.56%	650 64.87%	3.6794***
Stay	641 71.46%	589 65.66%	3.5445***
Start 22	24 58.54%	22 53.66%	0.7027

Employment variable	Pre-pandemic	Post-pandemic	Paired t-test
Start 21	31 68.89%	29 64.44%	0.5730
Back	11 57.89%	10 52.63%	0.4376
Public	106 69.74%	103 67.76%	0.4920
Stay	86 69.35%	88 70.97%	-0.3767
Start 22	8 72.73%	6 54.55%	0.8032
Start 21	4 57.14%	2 28.57%	1.5492
Back	8 80.00%	7 70.00%	1.0000
Freelance	356 69.80%	353 69.22%	0.2725
Stay	292 69.86%	289 69.14%	0.3012
Start 22	27 77.14%	25 71.43%	0.7020
Start 21	28 63.64%	32 72.73%	-1.4310
Back	9 69.23%	7 53.85%	0.8054
Part-time	156 65.55%	149 62.61%	1.0437
Stay	117 64.29%	111 60.99%	1.0000
Start 22	12 70.59%	12 70.59%	0.0000
Start 21	22 66.67%	22 66.67%	0.0000
Back	5 83.33%	4 66.67%	1.0000
No employment	486 66.76%	458 62.91%	2.2627**
Stay	416 66.67%	392 62.82%	2.0788**
Start 22	35 76.09%	30 65.22%	0.0579*
Start 21	30 63.83%	30 63.83%	0.0000
Back	5 45.45%	6 54.55%	-1.0000

*** p<0.01, ** p<0.05, * p<0.1

In addition to Table 2 and Table 3, we stratified our sample based on employment status and performed mean difference tests on our interested variables. We provided the results of these tests in Table 4 and Table 5. We found that the public official group has the highest proportion of long-term lonely people, whereas the part-time group has the lowest proportion (Table 4). Regarding post-pandemic loneliness, the freelance group has the highest proportion, while the part-time group has the lowest level (Table 5). However, the mean test analyses indicated that people, irrespective of their employment status, suffer from loneliness at a relatively similar level. This finding contradicted the results of previous studies [5-10]. Since the mean difference analysis failed to explain the hypothesised association between these loneliness statuses and employment status, we performed a regression analysis.

Table 4. Long-term loneliness, stratified by employment status.

Long-term loneliness	**Employment status**					**Total**
	Public	**Private**	**Freelance**	**Part-time**	**No**	
Yes	83	521	271	122	374	1,371
	54.61%	52.00%	53.14%	51.26%	51.37%	52.13%
No	69	481	239	116	354	1,259
	45.39%	48.00%	46.86%	48.74%	48.63%	47.87%
Total	152	1,002	510	238	728	2,630
	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Mean difference	***F = 0.21***					

*** p<0.01, ** p<0.05, * p<0.1

Table 5. Post-pandemic loneliness, stratified by employment status.

Post-pandemic loneliness	**Employment status**					**Total**
	Public	**Private**	**Freelance**	**Part-time**	**No**	
Yes	11	67	39	14	48	179
	7.24%	6.69%	7.65%	5.88%	6.59%	6.81%
No	141	935	471	224	680	2,451
	92.76%	93.31%	92.35%	94.12%	93.41%	93.19%
Total	152	1,002	510	238	728	2,630
	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Mean difference	***F = 0.21***					

*** p<0.01, ** p<0.05, * p<0.1

2.4 Method

Similarly to previous studies such as Khan and Kadoya [2], Khan et al. [3], and Kadoya et al. [4], our dependent variables: loneliness, long-term loneliness, and post-pandemic loneliness, are binary variables. As a result, we performed logit regressions on the following equations. We used full-time private workers as a base group to avoid the perfect multicollinearity problem.

$$(1)\ Y_{1i} = f(E_i, X_i, \varepsilon_i)$$
$$(2)\ Y_{2i} = f(E_i, X_i, \varepsilon_i)$$

where Y_1 is long-term loneliness, Y_2 is post-pandemic loneliness, E is a vector of work and employment status variables, X is a vector of other explanatory variables.

In addition to these equations, we also introduced equations with employment movement variables M where full-time private workers who started their job in 2021 are a base group. We also performed logit regressions on Equation (3) and Equation (4).

$$(3)\ Y_{1i} = f(E_i, M_i, X_i, \varepsilon_i)$$
$$(4)\ Y_{2i} = f(E_i, M_i, X_i, \varepsilon_i)$$

Our dataset has limitations. Table 2 revealed that our sample's average age is around 54 years old, which is older than the Japanese population on average [21]. Table 2 also revealed that most of our sample is male (69.70%), whereas only 48.61% of the Japanese population is male [21]. As a result, we performed weighted regression to counter such issues. We also conducted a robustness check with the add-drop variables method.

3. Results

Since several studies found that people had been suffering from loneliness long before the pandemic, we decided to perform a panel data analysis. We categorised loneliness into two main types: long-term loneliness and post-pandemic loneliness. The followings are our regression results for these two loneliness types.

3.1. Long-term loneliness

Table 6 provides the regression results of long-term loneliness. The main explanatory variables are work and employment status: public job, freelance job, part-time job, and no employment. We used a private job variable as a base to avoid the perfect multicollinearity problem. People with a freelance job are more likely to suffer from long-term loneliness than full-time private employees at a 95% significant level. The estimates of freelancers are robust and range between 0.355 to 0.432. People without employment are also more likely to suffer from long-term loneliness than full-time private employees at a 95% significant level. However, the estimates are not robust.

Table 6. Logit regression results of long-term loneliness (explanatory variables: work status variables).

Variables	Dependent Variable: Long-term loneliness			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Interested variables				
Private job	-	-	-	-
Public job	0.177	0.172	-0.0233	0.0423
	(0.242)	(0.243)	(0.250)	(0.247)
Freelance job	0.432**	0.355**	0.392**	0.422**
	(0.173)	(0.171)	(0.174)	(0.181)
Part-time job	0.123	-0.0510	0.0381	0.105
	(0.249)	(0.240)	(0.227)	(0.233)
No employment	0.328**	0.176	0.255	0.254
	(0.163)	(0.167)	(0.172)	(0.173)
Constant	0.362	4.133***	1.995	1.077
	(0.755)	(1.538)	(1.717)	(2.048)
Control				
Demographic characteristics	Y	Y	Y	Y
Household characteristics	Y	Y	Y	Y
Financial characteristics		Y	Y	Y

Variables	Dependent Variable: Long-term loneliness			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Behaviour and future anxiety characteristics			Y	Y
Physical health characteristics			Y	Y
Mental health characteristics				Y
Perception characteristics				Y
Observations	2,630	2,630	2,630	2,630
Log pseudolikelihood	-63,500,000	-63,200,000	-59,300,000	-58,100,000
Chi2 statistics	48.82	54.19	165.1	231
p-value	0.000	0.000	0.000	0.000

Robust standard errors in parentheses - *** p<0.01, ** p<0.05, * p<0.1

Table 7 provides the regression results of long-term loneliness where the main explanatory variables are employment movement variables. We used those who started a full-time private job in 2021 as a base group to avoid the perfect multicollinearity problem. Although the previous results (Table 6) revealed that private workers are not at risk of developing long-term loneliness problems, this panel data analysis provides the contrary. We found that full-time employees who have stayed in their job since 2020, who started their career in 2022, and who returned to their position in 2022 are more likely to suffer long-term loneliness at a 90% to 95% significant level. Meanwhile, we found that only one freelancer group is more likely to suffer long-term loneliness. Those who started their freelance job in 2021 are at risk of developing long-term loneliness problems at a 95% significant level. For the current part-timers, people who started their job in 2021 are more likely to suffer from long-term loneliness at a 90% significant level. In contrast, people who recently returned in 2022 are less likely to suffer from long-term loneliness. Regardless, the latter's estimates are not robust. For current public officials, people who have stayed in their job since 2020 and those who returned to their position in 2022 are more likely to suffer from the long-term condition at a 95% significant level. Finally, we found that people who stopped working in 2021 are more likely to suffer long-term loneliness at a 95% significant level.

Table 7. Logit regression results of long-term loneliness (explanatory variables: employment movement variables).

Variables	Dependent Variable: Long-term loneliness			
	Model 5	**Model 6**	**Model 7**	**Model 8**
Interested variables				
Stay (private job)	1.636*	1.660*	1.644*	1.683*
	(0.857)	(0.863)	(0.894)	(0.884)
Start 22 (private job)	2.063**	2.078**	2.325**	2.018**
	(0.967)	(0.970)	(1.046)	(0.982)
Start 21 (private job)	-	-	-	-
Back (private job)	1.869**	1.886**	2.089**	1.981*
	(0.949)	(0.959)	(1.045)	(1.034)
Stay (public job)	2.407**	2.374**	1.986*	1.887*
	(1.203)	(1.189)	(1.047)	(1.002)
Start 22 (public job)	0.573	0.558	0.309	0.122
	(1.402)	(1.406)	(1.267)	(1.212)
Start 21 (public job)	-0.474	-0.429	-0.253	-0.0871

Variables	Dependent Variable: Long-term loneliness			
	Model 5	Model 6	Model 7	Model 8
	(1.441)	(1.435)	(1.346)	(1.303)
Back (public job)	3.273**	3.242**	2.854**	2.773**
	(1.336)	(1.321)	(1.204)	(1.177)
Stay (freelance job)	0.0321	0.0314	-0.151	-0.0915
	(0.512)	(0.515)	(0.483)	(0.471)
Start 22 (freelance job)	0.218	0.228	0.0943	0.154
	(0.604)	(0.608)	(0.595)	(0.591)
Start 21 (freelance job)	2.027**	1.954**	2.154**	2.123**
	(0.974)	(0.980)	(0.995)	(0.986)
Back (freelance job)	-1.260	-1.304	-1.593*	-1.321
	(1.082)	(1.043)	(0.920)	(0.889)
Stay (part-time job)	-0.0690	-0.0114	-0.0571	-0.200
	(0.418)	(0.435)	(0.444)	(0.452)
Start 22 (part-time job)	0.227	0.212	0.176	0.0413
	(0.701)	(0.688)	(0.766)	(0.765)
Start 21 (part-time job)	1.889**	1.673*	1.780*	1.986**
	(0.916)	(0.927)	(0.965)	(0.960)
Back (part-time job)	-2.302*	-2.535*	-2.329	-2.552*
	(1.355)	(1.438)	(1.446)	(1.422)
Stay (no employment)	-0.314	-0.343	-0.405	-0.337
	(0.380)	(0.381)	(0.392)	(0.374)
Start 22 (no employment)	-0.363	-0.360	-0.558	-0.550
	(0.511)	(0.521)	(0.534)	(0.533)
Start 21 (no employment)	2.274**	2.141**	2.250**	2.207**
	(0.921)	(0.925)	(0.964)	(0.947)
Back (no employment)	-0.163	-0.0692	0.339	0.389
	(0.907)	(0.865)	(0.814)	(0.746)
Constant	-1.201	3.094*	0.904	0.0329
	(1.050)	(1.670)	(1.797)	(2.030)
Control				
Demographic characteristics	Y	Y	Y	Y
Household characteristics	Y	Y	Y	Y
Financial characteristics		Y	Y	Y
Behaviour and future anxiety characteristics			Y	Y
Physical health characteristics			Y	Y
Mental health characteristics				Y
Perception characteristics				Y
Observations	2,630	2,630	2,630	2,630
Log pseudolikelihood	-62,200,000	-61,900,000	-58,000,000	-56,900,000
Chi2 statistics	76.91	83.35	191.1	253.2
p-value	0.000	0.000	0.000	0.000

3.2 Post-pandemic loneliness

We studied post-pandemic loneliness and calculated the estimates of Equation (2). The regression results of post-pandemic loneliness are provided in Table 8. Unfortunately, we could not perform regression analysis on Equation (4) due to the low number of observations who suffered from post-pandemic loneliness. Overall, we found that the associations between employment variables and post-pandemic loneliness are insignificant at a 90% significant level.

Table 8. Logit regression results of post-pandemic loneliness (panel data analysis).

Variables	**Dependent Variable: Post-pandemic loneliness**			
	Model 9	**Model 10**	**Model 11**	**Model 12**
Interested variables				
Private job	-	-	-	-
Public job	0.0897	0.0920	0.0875	0.0502
	(0.398)	(0.401)	(0.396)	(0.400)
Freelance job	0.210	0.208	0.233	0.229
	(0.306)	(0.302)	(0.297)	(0.304)
Part-time job	-0.618	-0.637	-0.568	-0.620
	(0.418)	(0.432)	(0.422)	(0.429)
No employment	-0.116	-0.118	-0.0549	-0.0659
	(0.316)	(0.314)	(0.311)	(0.313)
Constant	-1.436	-0.538	-0.586	-0.496
	(1.020)	(2.944)	(3.254)	(2.956)
Control				
Demographic characteristics	Y	Y	Y	Y
Household characteristics	Y	Y	Y	Y
Financial characteristics		Y	Y	Y
Behaviour and future anxiety characteristics			Y	Y
Physical health characteristics			Y	Y
Mental health characteristics				Y
Perception characteristics				Y
Observations	2,630	2,630	2,630	2,630
Log pseudolikelihood	-24,500,000	-24,500,000	-24,400,000	-24,300,000
Chi2 statistics	22.02	23.97	30.86	33.58
p-value	0.0242	0.0462	0.0208	0.0291

Robust standard errors in parentheses - *** p<0.01, ** p<0.05, * p<0.1

4. Discussion

Although people with different work and employment movements have somewhat similar tendencies to feel lonely, their loneliness can stem from different origins. Freelance workers tend to suffer long-term loneliness because these workers are more independent and less likely to receive support from colleagues. Lack of social support can lead to loneliness issues and depressive symptoms [5,9]. Regrettably, we cannot provide a detailed explanation of the freelancers' movement due to insufficient statistical power. Since freelancers might be among the most at-risk groups, future studies may need to collect more observations to study these groups in detail. While considering movement in the labour market, we found that public workers tend to feel lonely. Although COVID-19 was not a pandemic yet during the survey period in 2020, its rapid spread around the world and in Japan has increased a series of social issues requiring government intervention. As a result, the workload of public officials must be increased accordingly. Even though public employment is highly secured, the increasing workload might contribute to the loneliness among public officials since 2020.

Meanwhile, we found that furloughed public workers, who worked in 2020, left in 2021, and returned to the sector in 2022 are more likely to suffer long-term loneliness. These findings supported Morrish and Medina-Lara's [22] argument that loneliness and unemployment have a bi-directional relationship. These workers already felt lonely in 2020, and the loneliness may reduce their productivity. This reduced productivity might make them be among the first group of workers made redundant during the pandemic. Then, job uncertainty may contribute to their loneliness in 2021. Later, prejudice or a perceived prejudice against these workers may keep their loneliness persist. Returning to work after being furloughed can cause an embarrassment for the workers. Due to the collectivism in Japan [13], furloughed workers might perceive themselves or be perceived by their colleagues as the weakest link or a free rider. These perceptions may cause social isolation, leading to loneliness after their return. We found that Morrish and Medina-Lara's [22] argument may also contribute to the movement of those who became freelancers, part-timers, or non-workers in 2021. These workers might have secured jobs while experiencing loneliness before the pandemic. Since loneliness might affect their productivity, they became one of the first groups of workers who were laid off during the unfolding of the pandemic. The job insecurity might induce their loneliness in 2021. Some might suggest that changing from a secure to an unsecured job contributed to long-term loneliness problems. However, the absence of the effect of starting a freelance and part-time career in 2022 implies that the timing of switching jobs may have some contribution. Starting a highly unsecured job during an uncertain time like the pandemic might limit support for those other new freelance workers and part-timers would typically receive during the non-pandemic time.

Not everyone can get back on their feet. Those who stopped working since 2021 may become unemployed or become homemakers later. In terms of loneliness among unemployed people, this finding is consistent with Bjelajac et al. [23], Bu et al. [24], Largaard et al. [25], Li and Wang [26], and Shiota et al. [10]. They found a significant association between unemployment and loneliness. Intrinsically, unemployment can cause social isolation and declining self-esteem, which ultimately cause people to feel lonely [22]. In terms of loneliness among homemakers, this finding is consistent with other studies' narratives. Housewives are more likely to have lower psychological well-being [27-30] and have a higher risk of developing mental health problems [27,31]. Like freelance workers, these homemakers might not receive enough support from others [27]. Homemakers typically have demanding emotional work while receiving a lower direct financial return. Ultimately, homemakers might be more likely to feel lonely than others. Regardless, our study did not directly compare homemakers or unemployed people to other groups due to insufficient statistical power.

Private workers are probably the most at risk of developing long-term loneliness problems. Initially, we found that full-time employees generally are not likely to have long-term loneliness. However, full-time employees who have stayed in their job since 2020, who started their careers in 2022, and who returned to their position in 2022 are more likely to suffer long-term loneliness. This finding is consistent with the narrative on working culture in Japan, which is infamous for the high-stress environment [13] and low pay [32,33]. Combining these factors with long working hours, these workers might feel isolated and suicidal [11-14]. In extreme cases, these workers experience Karoshi or death by overwork. Due to the seriousness of this issue, we encourage future studies to explore loneliness among private workers in detail.

Finally, we found that people who returned to their part-time job in 2022 are less likely to become lonely at a 90% significant level. The expectation toward part-time workers might differ from that of full-time workers. As a result, furloughed part-time workers may not experience social isolation like full-time workers. Furthermore, most part-time workers are women [34]. Most of them are secondary income earners [35-38] and were the most affected during the layoff in 2020 [34,39]. Being able to return to their work may reduce their anxiety about their household financial issues. Moreover, returning to work allows them to socialise better than staying home. Thereby, returning to their part-time job reduces their likelihood of feeling lonely.

The study has some advantages over other studies. This study is among a few studies that utilised the panel survey to study loneliness issues among workers in Japan. This panel survey enabled us to measure workers' loneliness levels before the announcement of the pandemic until the post-pandemic, which ultimately helped us to observe the long-term loneliness among the workers. Furthermore, the panel survey allowed us to track the movement of people in the labour market during the pandemic and post-pandemic. As a result, we could find associations between loneliness and movements in the labour market. Meanwhile, this study is one of a few studies that measured loneliness among people with different job and employment characteristics. These advantages allowed us to identify the most vulnerable groups in the labour market and provide guidelines for developing countermeasure policies. These advantages also fulfil research gaps and offer an approach for future studies.

This study is not without limitations. Firstly, our data are not multidimensional in measuring people's experiences during the pandemic. Some people may lose a loved one and currently experience grief during the pandemic. These unobserved characteristics may influence our results. Second, although our sample size is larger than other cross-sectional studies, our sample is still somewhat small and lacks some statistical power. As a result, we cannot perform subsample analysis and study the characteristics of workers in detail. Third, we mentioned earlier that our sample is skewed. The male gender ratio and the average age are relatively higher than the national statistics [21]. We addressed this problem by using weighted regression analysis. Then, we performed a robustness check and found that the findings were mostly robust. After comparing our results with other literature, we found that our findings are consistent.

5. Conclusions

This study examined an association between long-term loneliness and work and employment status in Japan through HiHER's panel survey. We measured workers' loneliness levels before the pandemic's announcement in 2020 until the post-pandemic in 2022. We also tracked the movement of people in the labour market during those times. We found that freelance workers are vulnerable to developing long-term loneliness conditions. Being more independent might influence freelance workers to receive less support from their colleagues. The pandemic might even also reduce the support further. Regardless, the insufficient statistical power led to the absence of significant associations between employment movements and loneliness among freelancers, which ultimately obstructed us from investigating this group further. Meanwhile, we observed other employment movement variables and found that full-time private workers are the most vulnerable to long-term loneliness conditions. Most of their movements are positively associated with long-term loneliness issues. This finding supported concerns about the working culture in Japan, which is the product of the intertwining between the Japanese culture and its employment system [13]. Finally, the finding on other employment movements may suggest the bi-directional relationship between loneliness and unemployment. Unfortunately, we did not explore this relationship further because of the lack of detailed information on unemployment. Since our findings revealed the heterogeneous associations between different types of work and employment and loneliness, one-size-fits-all policies may not solve loneliness problems among workers in Japan. We recommend that policymakers consider these differences among workers and tailor policies appropriately.

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