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Research Paper

Physical isolation and loneliness: Evidence from COVID lock-downs in Australia☆

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ABSTRACT

Loneliness contributes to mortality risk, comparable to the risks associated with smoking and obesity, although the causal determinants of loneliness remain less clear. This paper leverages mandatory stay-at-home orders in Australia as a natural experiment and employs data from a panel study to investigate the causal link between physical isolation and loneliness. By analyzing variations in the number of lockdown days experienced by respondents up until their interview dates, and utilizing difference-in-differences analyses with individual, region, and year fixed-effects estimations, we find, contrary to expectations, that the number of days in lockdown does not significantly impact loneliness. Our study examines cumulative, concurrent, and non-linear effects, and assesses external validity through community morale and peer effects during lockdowns using spatial analysis. Additionally, we delve into heterogeneous effects across various factors, such as income, age, personality, living arrangements, and remoteness, finding statistically and empirically insignificant effects. However, for extroverts and young people, we observe weak statistical significance. We investigate exclusion restrictions by analyzing factors including social contacts, internet access, job industry, and household characteristics in relation to loneliness; as well as time use and relationship satisfaction to better understand the underlying mechanism. Our study challenges the notion that 'being alone' and 'being lonely' are interchangeable concepts, providing the first empirical causal evidence of no links between the two. Furthermore, our findings refine earlier understandings of social isolation, highlighting that it likely encompasses factors beyond physical isolation.

> "Cities can be lonely places, and in admitting this we see that loneliness doesn't necessarily require physical solitude, but rather an absence or paucity of connection, closeness, (and) kinship…"
>
> Olivia Laing, *The Lonely City*

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1. Introduction

Loneliness is a pervasive issue affecting society on social, health, and economic levels (Cacioppo and Cacioppo, 2018; Murthy, 2020). Notably, the mortality risk linked to loneliness rivals that associated with obesity, smoking, alcohol consumption, and drug use (Holt-Lunstad et al., 2015). Consequently, gaining a deeper understanding of the roots of loneliness is essential for designing interventions that enhance public health, mitigate social exclusion, and minimize healthcare costs.

Laursen and Hartl (2013), Vanhalst et al. (2013), and Weiss (1975), among other prior research on physical isolation and loneliness, have primarily provided correlational evidence, lacking causal insights. This limitation arises because these studies cannot randomize individuals into isolation. To address this gap, we leverage the COVID lockdown in Australia as a natural experiment to explore the causal relationship between physical isolation and loneliness.

We choose Australia as our study location due to several distinctive features of its lockdown policies. Firstly, the country's geographic isolation facilitates the effective implementation of stringent COVID lockdown measures, resulting in high compliance rates and enhancing the validity of exogenous physical isolation. Secondly, Australia imposed a more prolonged lockdown period compared to many other high-income countries, allowing us to capture up to 154 days of lockdown in the 2020 wave alone.[1] This substantial variation in treatment time forms the basis for our causal identification. Thirdly, Australia maintained a relatively COVID-free status in 2020, reducing the confounding effects of COVID contraction on loneliness.

We utilize rich individual panel data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, which we merge with the number of lockdown days at the geographical unit level corresponding to lockdown policies. We conduct difference-in-differences (DID) analyses using a continuous treatment that varies across individuals. Our identification relies on the fact that the number of lockdown days individuals experience up until their survey interview dates is randomly assigned and unrelated to individual characteristics. Additionally, we employ three-way fixed effects in the model to control for any unobserved heterogeneity at the individual, year, and regional levels. We validate our identification by (1) testing the random assignment of lockdown days against income, education, and health status; (2) performing balance tests for pre-lockdown characteristics between treated and control groups; and (3) conducting an event study to support the common trend assumption.

Our findings indicate that physical isolation has little effect on loneliness. Point estimates suggest that 100 days of lockdown increase loneliness by only 2.1% of a standard deviation (SD), and these estimates are statistically insignificant across all specifications. To contextualize these results, we compare the lockdown effect on loneliness to the effect of a well-established risk factor for loneliness—widowhood—which increases loneliness by 49% of a SD. Furthermore, we compare it to a lockdown effect on mental health using the same identification, which significantly decreases mental health by 13% of a SD.

We investigate whether the level of loneliness is persistent or transitory by examining concurrent and cumulative effects on individuals and find no significant variations over time. We also test for exclusion restrictions through household characteristics, health status, work factors, frequency of social interactions, COVID statistics, and macroeconomic trends (e.g., income per capita and population), and our results remain consistent after controlling for these confounders.

Additionally, we specifically test the external validity of physical isolation using COVID lockdown by examining community morale and the proximity of peers who are not in lockdown. We do not find evidence that the lockdown, as a general phenomenon, changes community satisfaction, which could potentially offset loneliness. Furthermore, spatial analysis indicates that people do not anchor their feelings of loneliness based on peers who are outside the lockdown borders. This provides evidence that COVID lockdowns proved to be a valid quasi-experiment on physical isolation.

Heterogeneous treatment effects reveal little difference across gender, living arrangements, remoteness, income, immigrant status, and indigenous population. We identify weak significance for an increased level of loneliness among individuals aged 15–25 and those who are extroverted. Additionally, we examine whether already lonely people are more likely to be affected and conduct robustness analyses by using (1) different thresholds for lockdown days; restricting samples to (2) individuals living alone, (3) those who have not moved, and (4) sample of major cities; and (5) extra data from the 10 prior waves. We also present intensive and extensive margins, and study long-term effects of COVID lockdown. All results find no significance of lockdown days on loneliness.

The COVID-19 pandemic has profoundly impacted various aspects of economic well-being, leading to a growing body of literature that utilizes COVID lockdowns as an exogenous shock. For instance, Clark & Lepinteur (2022) demonstrate that lockdowns decrease life satisfaction in five European countries by employing individual fixed effects. Ravindran & Shah (2020) uncover a positive effect of COVID lockdowns on domestic violence against women in India through DID analysis of aggregate data on the regional intensity of government-mandated lockdowns. Meanwhile, Butterworth et al. (2022) focus on the Australian State of Victoria as the treated group during the 2020 treatment period, revealing that lockdowns negatively impact mental health using dichotomous DID with individual fixed effects.[2]

Several prior studies have investigated the impact of COVID lockdowns on loneliness. For example, Grimes (2022) utilized repeated cross-sectional individual-level data during the pandemic and employed a difference-in-difference method to assess well-being measures, including loneliness. This analysis considered four stringent levels of lockdown while controlling for quarterly time fixed effects, revealing a positive association between increased loneliness and the implementation of more restrictive lockdown measures.

[1] We also investigate the long-term effects by including data from the years 2021 and 2022 in the Appendix. The maximum number of lockdown days observed in the long-term effect estimation is 262 days.

[2] More studies have estimated the general COVID effects, as opposed to only the effect of lockdowns. For example, Lepinteur et al. (2022) use the German Socio-Economic Panel, find that COVID increases loneliness in women and it partially explains the gender gap in life satisfaction.

In a similar vein, Caro et al. (2022) examined a European dataset using a dynamic mixture model to estimate loneliness across subpopulations. Their findings indicated that older individuals were less likely to experience loneliness but were more affected by lockdown measures. Conversely, young people living alone reported high levels of loneliness but were unaffected by lockdowns. Additonally, Schurer et al. (2022) employed a difference-in-differences analysis to study loneliness and other outcomes, with Melbourne designated as the treated group, Sydney as the control group, and 2020 as the treated period, drawing on the HILDA dataset. Their analysis included categorized durations of exposure to lockdown. While loneliness among mothers increased by 0.27 standard deviations, most vulnerable groups remained unaffected. In contrast to these studies focusing on onset lockdown effects, Serrano-Alarcón et al. (2022) explore the association between *easing* COVID lockdown measures and mental well-being. Utilizing a difference-in-difference analysis and exploiting variations in policy responses between England and Scotland, the study finds that the relaxation of lockdown measures leads to rapid improvements in mental health, but no effect of lockdown on loneliness.

The novelty of our study lies in the following aspects. Firstly, we establish a more robust causal inference compared to previous studies by incorporating both regional-level policy variations and individual-level interview timing. This also yields richer variation in lockdown intensity than the dichotomous treatment used in the previous studies. By employing a rigorous Difference-in-Difference methodology with individual, regional, and yearly fixed effects, we effectively mitigate confounding factors such as reverse causality from socioeconomic and demographic factors.

Secondly, our study utilizes nationally representative longitudinal data encompassing 17,124 individuals, providing extensive individual background information and regional economic statistics. This comprehensive dataset enables before-after comparison, and facilitates the generalization of results at a national level.

Thirdly, we thoroughly investigate various aspects that could potentially affect causal inference, including household structure, health status, work arrangements, social interactions, time use, and macroeconomic factors. Additionally, we examine peer effects and community satisfaction to enhance the external validity of our findings. In doing so, our study offers a comprehensive and in-depth analysis of the effects of lockdown measures.

This paper contributes to the existing literature on the impact of the COVID-19 pandemic on economic well-being. While a booming body of studies has explored the effects of COVID-19 lockdowns on mental health, life satisfaction, and incidents of domestic violence (e.g., Butterworth et al., 2022; Clark and Lepinteur, 2022; Ravindran and Shah, 2020), relatively few have examined loneliness (Grimes, 2022; Schurer et al., 2022; Serrano-Alarcón et al., 2022). Although these existing studies offer valuable insights, our research builds upon them by employing a more robust methodology to establish causal inference. We do so by (1) analyzing regional-level policy variations alongside individual-level interview timing; (2) By specifically considering the exact number of lockdown days, we are able to evaluate a nationally representative sample with greater precision, improving upon city or state level studies that employs a crude dichotomous treatment effect; (3) Through the rigorous application of a Difference-in-Differences methodology, incorporating individual, regional, and yearly fixed effects, we effectively mitigate potential confounding factors such as reverse causality from physical health, socioeconomic status, and demographics.

Furthermore, our study contributes to the literature on the determinants of loneliness. Previous literature associates social isolation with loneliness (Cohen-Mansfield et al., 2016; Demakakos et al., 2006), and primarily focuses on specific subgroups of the population, such as older adults or adolescents, and often utilizes small sample sizes to establish correlational effects (Laursen and Hartl, 2013; Vanhalst et al., 2013). Our research presents the first empirical causal evidence suggesting that physical isolation alone does not always lead to increased loneliness, except for young people and extroverted individuals. Moreover, we investigate other potential factors influencing loneliness. For example, we demonstrate that social contacts can alleviate loneliness, while peer effects do not appear to play a significant role. These findings deepen our comprehension of loneliness determinants, clarify the differentiation between physical isolation and social isolation, and provide valuable insights for policymakers and researchers seeking to develop effective interventions to address this issue.

The remainder of this paper is organized as follows: Section 2 discusses the literature review on physical isolation and its distinction from social isolation in its effects on loneliness. Section 3 introduces our data and sample, followed by Section 4, which presents the methodology. Section 5 discusses the results, while Section 6 extends to heterogeneous results, mechanisms, and other robustness checks. Finally, Section 7 concludes and discusses avenues for future research.

2. Literature review

The COVID-19 pandemic has had far-reaching consequences on all aspects of daily life, with the restrictions imposed during the early phase of the pandemic leading to increased social isolation and loneliness (Teater et al., 2021). Pandemic conditions presented a major stressor on adults' well-being and loneliness (Heidinger and Richter, 2020), and due to the nature of the pandemic—which placed individuals at increased risk of sickness and fatality—protective measures, such as stay-at-home orders and lockdowns, may have been perceived as particularly isolating (Krendl and Perry, 2021).

2.1. Difference between loneliness and social isolation

Although loneliness and social isolation are often used interchangeably, they are two separate, albeit interrelated, concepts. Loneliness is a subjective measure that refers to a discrepancy in individuals' desired and actual social relationships in quality and quantity (de Jong-Gierveld et al., 2006). It can be further divided into *emotional* and *social* loneliness, in which the former refers to the absence of a close emotional attachment and the latter to the absence of broader social network relationships (Weiss, 1975). Conversely, social isolation is an objective measure of an individual's lack of relationships that forms a continuum from social isolation

to social participation (de Jong-Gierveld et al., 2006). Social isolation can be measured through factors such as the size and structure of social networks. It can also be measured through the extent of social support received, the frequency and duration of interactions, or the level of social engagement with the community (Cornwell and Waite, 2009). Perceived social isolation is also discussed in the literature but is commonly used as a synonym for social loneliness because it is a subjective measure of social contacts and support (Shankar et al., 2011). Arguably, social isolation has also frequently been conflated with physical isolation.

Loneliness and social isolation are distinguished from one another to reflect the reality that the two concepts do not necessarily co-occur; individuals can experience one, both, or neither (Russell et al., 2013). Individuals may be completely socially isolated—for instance, living alone and kilometers from their nearest neighbor—but experience no loneliness. Similarly, an individual may be surrounded by many types of relationships and social supports but feel lonely. Although the concepts differ, they are correlated (Benson et al., 2021; Coyle and Dugan, 2012). Nevertheless, it has traditionally been difficult to tease out their relations due to reverse causation and observed and unobserved confounders. In other words, those who are lonely may prefer to be alone. There may also be individual factors that are correlated with both loneliness and physical isolation.

On the link between loneliness and social isolation, Leary et al. (2003) found that the frequency and enjoyment of solitary activities are more strongly related to a desire for solitude than a desire to spend time away from people. Solitary activities can provide a respite from excessive social interaction, are beneficial for psychological well-being, and do not necessarily indicate loneliness. However, engaging in solitary activities has been found to suffer from the Goldilocks effect. This refers to individuals who need to engage in a suitable number of solitary activities for their well-being: Too many or too few social connections might result in negative well-being. Russell et al. (2013) also found this effect in adolescents' relationships whereby loneliness increased the further an individual was from their desired level of relationships. This association exists both when an individual has fewer desired relationships and when they have more, and demonstrates that the association between loneliness and social isolation is nonlinear, since negative feelings increase the further an individual is from their desired level of social connections in either direction (Russell et al., 2013)

Interestingly, both loneliness and social isolation are commonly associated with the same health indicators. Studies have found separate associations between loneliness and social isolation with a range of health concerns after controlling for each other. Research has investigated the links between loneliness and social isolation, as well as frailty (Davies et al., 2021; Gale et al., 2018), mortality (Lennartsson et al., 2022), physical activity (Schrempft et al., 2019), inflammation (Smith et al., 2020), cardiovascular events (Bu et al., 2020), sleep quality (Benson et al., 2021), mental health (Christiansen et al., 2021; Ge et al., 2017), and hearing loss (Shukla et al., 2020). While this list is not exhaustive, it helps illustrate the recent frequency of using both measures synonymously in a study. The range of studies that investigate the association of loneliness and social isolation with varying health indicators highlight the interrelatedness of the two concepts; therefore, both must be considered together in research and when proposing interventions to mitigate risk (Holt-Lunstad et al., 2015). Holt-Lunstad et al. (2015) found that a large proportion of the empirical literature did not account for both loneliness and social isolation, and often accounts for only one concept or used a measure that combined the two, which reveals a weakness in their meta-analytic review. Although studies are now better at separating loneliness and social isolation measures, incorporating both is required to elucidate their association with each other and other variables. This also leads to a complicated interpretation because they rarely change independently of each other.

2.2. Loneliness and social isolation during COVID-19

During the pandemic, restrictions negatively impacted both loneliness and social isolation, as the objective experience of social distancing and stay-at-home restrictions forced individuals worldwide to remain at home for unprecedented intervals. Consequently, feelings of isolation have increased: Individuals report feeling deprived and restricted in their daily activities (Gonçalves et al., 2022); having reduced life satisfaction, well-being, and connection with their community (Clair et al., 2021); and experiencing a decrease in network density and size (Kovacs et al., 2021). The nature of COVID-19 specifically required that people isolate from each other, which increased the physical distance between individuals and their networks. This, in turn, could potentially induce feelings of loneliness.

Kovacs et al. (2021) found that while loneliness increased, people with more than five social contacts in their core network and those who had long and frequent contact with them had a smaller increase in loneliness. This demonstrates the phenomenon of 'turtling up' in networks, whereby during stressful events individuals focus on the stronger ties in their network. Among young adults, contact with friends and relationship quality increased over the pandemic and protected against loneliness (Juvonen et al., 2022). In New Zealand, higher socioeconomic status and greater social participation were also associated with less loneliness (Lay-Yee et al., 2022). Regarding activities during the pandemic, Pauly et al. (2022) found that spending more alone time than usual was associated with loneliness over their 10-day study period. This relates to what is already known about loneliness and the Goldilocks effect: When solitary time is unwarranted loneliness increases.

In cross-sectional studies, loneliness and social isolation rose for every age group. However, loneliness and social isolation were the greatest among young adults (Clair et al., 2021; Juvonen et al., 2022; Teater et al., 2021), as well as depression and anxiety (Juvonen et al., 2021). Technology and internet usage were identified by respondents as the most frequent way social needs were met (Gonçalves et al., 2022; Teater et al., 2021), and mediated the effects of the pandemic (Juvonen et al., 2021). Specifically, across a sample of 18- to 70-year-olds, satisfaction with (rather than frequency of) electronic contact was associated with lower levels of loneliness, depression, and anxiety (Juvonen et al., 2021). While young adults are consistently highlighted as experiencing greater loneliness over the pandemic, they have also been shown to be adaptive, employing the widest range of technologies to maintain meaningful connections during the pandemic (Juvonen et al., 2022; Teater et al., 2021). Hence, COVID-19 restrictions isolated people in their homes away from their social networks for an unprecedented period of time. As a result, life satisfaction and well-being have decreased alongside the rise in loneliness and social isolation across the population. However, closer ties with important social contacts have protected

individuals against greater increases in both measures.

In this study, we provide a unique account of how the physical isolation imposed during lockdowns may (or may not) have impacted loneliness in the general public. By exploiting variation in the number of days mandated due to COVID outbreaks we test whether the number of days in lockdown causes loneliness. We also examine variation by individual characteristics to determine whether the relationship differs for different groups of adults.

3. Data

3.1. Dataset and sample

Our data are from the Household, Income and Labor Dynamics in Australia (HILDA) Survey, which is a nationally representative household panel study that collects demographic and socioeconomic information and covers well-being, the labor market, and family characteristics. It is conducted by the Melbourne Institute: Applied Economic & Social Research and funded by the Australian government through the Department of Social Services. Besides the rich household characteristics, a novel feature of HILDA is that it captures individuals' reports of loneliness every year for those aged 15 years and above. This enables us to capture loneliness prior to the year 2020 COVID lockdowns as well as during the long periods of COVID lockdowns implemented in Australia. Along with the nationally representative nature of the survey, the dataset enables the before-after and treated-control double differences identification proposed in the paper.

We limit the study period to the years 2018, 2019, and 2020. The sample is restricted to individuals who have repeated loneliness measures in the HILDA survey.[3] We observe 17,124 individuals in the sample, with 13,946 in the treated group and 3230 in the control group.[4]

3.2. Key variables

The HILDA provides a general loneliness measure that asks, '*How much do you agree or disagree: I often feel very lonely*' (1=*strongly disagree* and 7= *strongly agree,* mean = 2.69 and SD = 1.76). Mund et al. (2020); Tani et al. (2020); Wister et al. (2016) and other studies use this variable to study loneliness in the Australian population. Though this is a single-item measure, Newmyer et al. (2021) validated the reliability of this question and that it is well-equipped to measure loneliness. Fig. 1 displays the loneliness measures among the treated and control groups by year. The distribution between the treated and control groups remains largely consistent over the course of the study period, with no significant variation observed between the groups. We will use the standardized measure for the purpose of cross-comparison with other studies on loneliness and economic well-being.[5]

3.3. Australian state lockdowns

In addressing our research question focused on physical isolation, we exclusively concentrate on the most stringent level of lockdown, which coincidentally aligns with the predominant lockdown policy in Australia (McCosker, 2021). This specific measure effectively compels individuals into physical isolation. Other forms of lockdown, such as restrictions on large gatherings, are not directly related to the physical isolation under examination in this paper.

The days each Australian state spent in lockdown between January 1, 2020, and February 21, 2021 (concluding the data collection for the 2020 wave), were initially compiled through a general Google search, and then a search of each state government's media release archives. The criteria for lockdown and lockdown duration were as follows: (1) only the days individuals were under legislatively enforced orders to stay home were included, and (2) during that period, individuals were only permitted to leave their homes based on four essential categories: shopping for essentials, work or education that could not be done remotely, medical or compassionate reasons, and outdoor exercise. When individuals were permitted to undertake an activity that did not fall into one of these four categories, the lockdown was considered to have ended.

The compliance of the treated and control groups in the quasi-experimental setting could potentially bias the estimation. In Australia, there are strict legal reinforcements on the lockdown (Auton and Sturman, 2022; Bleakley, 2021), therefore treatment group would adhere high level of physical isolation. Regarding the control group, it could be the case where people without lockdown still carry out voluntary home isolation (Hellmann and Thiele, 2022). While we do not directly observe this in the data, the potential

[3] We present results in which we restrict samples to individuals who had not moved between 2019 and 2020 (*N = 1,739 excluded*) in Appendix I. The results are highly consistent.

[4] The HILDA full sample comprises 27,473 distinct respondents in the waves spanning from 2018 to 2020. Among them, 22% are younger than 15 years old, rendering them ineligible for loneliness questions. Additionally, the sample excludes 6% of respondents who did not answer any loneliness questions, and 8% who answered only once, resulting in the inability to estimate individual fixed effects for these cases. Observations with missing values in control variables are also excluded from our analysis (7%). On average, the self-completed questionnaire has an average completion rate of about 95% per year from 2018 to 2020.

[5] As a complement to the standardized loneliness measure, we also include the ordered logit regression using the raw Likert scale for baseline estimation in Panel A of Table A3, and present its average marginal effects across responses ranging from 1 to 7 points in Panel B of Table A3 in the Appendix. The results show no significant changes from our baseline results and no significant changes beyond the average.

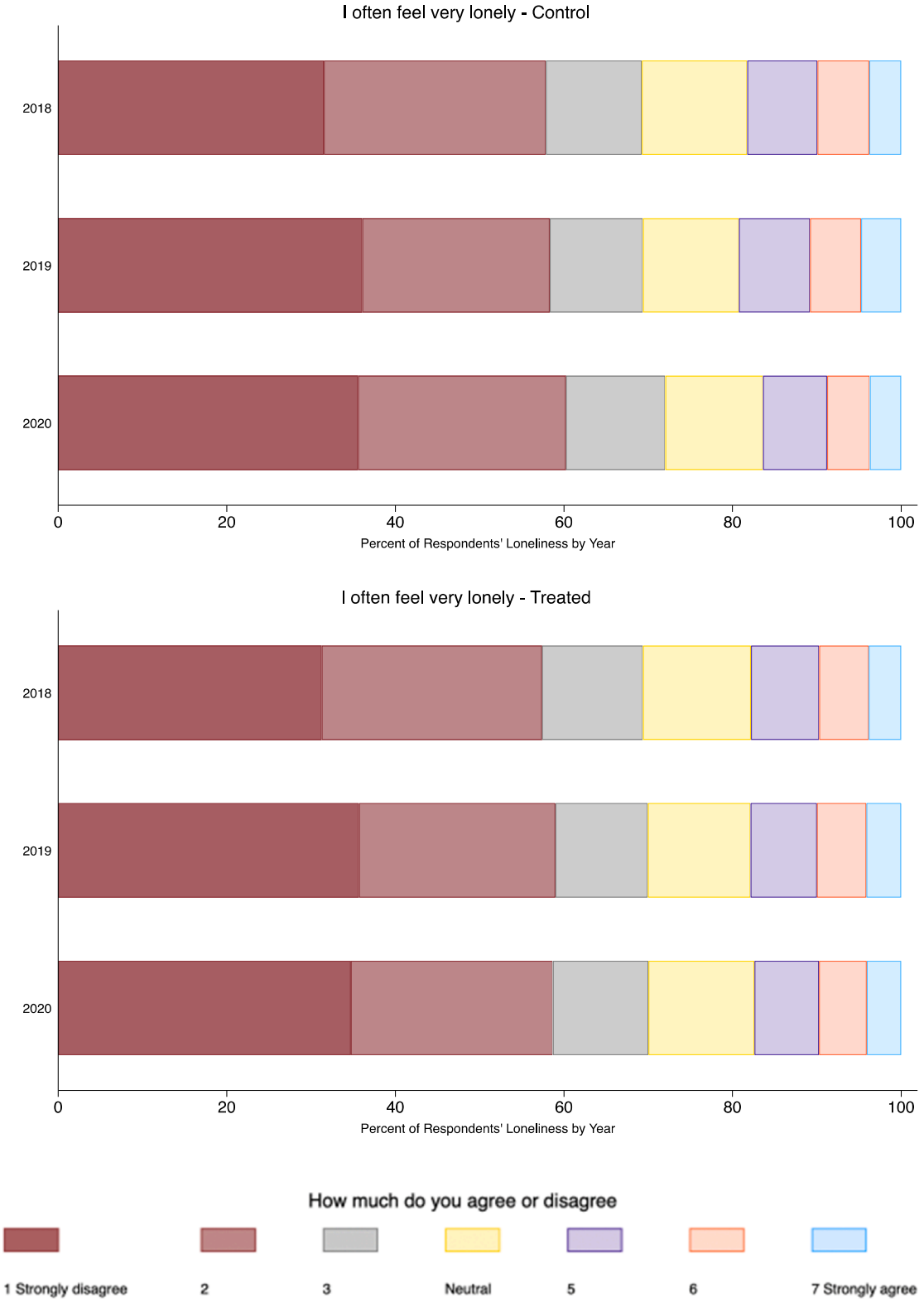

Fig. 1. Loneliness by year.
Source: HILDA 2018, 2019, and 2020 waves. Respondents with repeated loneliness measures. $N = 3230$ (Control) and 13,946 (Treated).

voluntary physical isolation in the control group would reduce the gap between the treated and control, making the measured treatment intensity lower than the actual intensity, which results in a lower bound estimation of lockdown effects on loneliness.

Table A1 summarizes lockdown days by the Greater Capital City Statistical Area (GCCSA), which separates state capitals from regional areas in the states. Notably, the most significant lockdown period during the study period was the second wave of lockdowns in Greater Melbourne, which lasted 111 days.

3.4. Treatment definition and treated and control groups

We merge the HILDA data with the lockdown measure by interview date. Lockdown days are defined as the total cumulative number of lockdown days in the specific region that the respondent had experienced up until their interview dates. Interview dates for the HILDA 2020 wave range from August 3, 2020, to February 21, 2021.[6] Therefore, all affected regions would have experienced at least the first wave of lockdowns in 2020. Fig. 2 presents the maximum lockdown days experienced by HILDA respondents by region, which shows that treatment intensity varies significantly.

We define the treatment of lockdown days starting from the 7th day for two reasons: First, short-term lockdowns would not impact loneliness levels, and second, empirically, this threshold enables us to count people in Adelaide and Western Australia as being in the control group as these states did not experience significant lockdown during this period. This provides more observations in the control group in order to conduct the parallel trends analysis necessary to validate our DID. However, it's worth noting that our baseline model, which employs a continuous treatment, is not contingent on the size of the control group. We also conduct a sensitivity test using the raw lockdown days for the treatment variable in Section 6.3 and the results do not change (see Table 11 Panel B).

The treated group is defined as respondents who live in lockdown states (i.e., lockdown days above 7 days). These states include the Australian Capital Territory (ACT), Victoria (VIC), New South Wales (NSW), Queensland (QLD), and Tasmania (TAS). The control group is defined as respondents who live in lockdown-free states (i.e., lockdown days are equal to or less than 7 days). These states are Northern Territory (NT) and South Australia (SA), Western Australia (WA).

Australia's states exhibit a greater degree of homogeneity compared to their counterparts in the United States, facilitating a more robust comparison between the treated and control groups. From an economic standpoint, the overall income distribution in Australia is notably less unequal than in the United States. This is evidenced by the Gini index, which stood at 34.3 in Australia and a considerably higher 41.4 in the U.S. during the pre-treatment period of 2018 (World Development Indicators, World Bank). Furthermore, Australia's provision of universal healthcare ensures a more equitable distribution of mental and physical health resources across states compared to the United States (Hall, 1999). This healthcare accessibility contributes to a reduction in health disparities among states, adding another layer to the comparative advantage of utilizing Australia as a context for the study.[7]

In our sample, the control group contains 19% of respondents, and the treated group 81%. The treatment intensity varies both across and within states. For instance, respondents in Victoria encountered a range of lockdown days up until their interview dates, spanning from 43 days to 154 days, and on average, the treated group experienced 53 days of lockdown in the 2020 wave (SD = 25), with a minimum of 33 days and a maximum of 154 days in lockdown.

4. Methodology

4.1. Assumptions of difference-in-differences

A difference-in-differences analysis requires three assumptions. We list them below, along with our strategies for validating the assumptions.

1. Trends in the affected states and non-affected states would have been similar in the absence of the reform. To test this assumption, we (1) compare pre-COVID characteristics in affected and non-affected regions, (2) plot the average of loneliness in affected and non-affected regions over years, and (3) use an event study to test their pre-existing trends in a regression.
2. Lockdown only affects treated states, not untreated states. To satisfy this condition, (1) we include year fixed effects to capture any common trends in the affected states and non-affected states and lockdown days to capture any additional effects on those who experienced lockdowns. (2) To prevent lockdown-induced interstate immigration[8] as well as economic shocks, we include population and income per capita at state-year level from the Australian Bureau of Statistics in our robustness tests (Section 5.5).
3. No other factors could be systematically correlated with both the number of lockdown days and loneliness in the affected region. To address this concern, we (1) test the random assignment of lockdown days by regressing it against the three most 'suspicious factors' that could potentially correlate with individual characteristics (see Section 4.4) and (2) control for confounding factors in terms of household, health, work, social, COVID-19, and macro factors (Section 5.5).

[6] Lockdown days in 2021 are tallied cumulatively with those from 2020.

[7] We conduct further tests by excluding certain states/territories that might be considered outliers, as detailed in section A2.1 in the Appendix. However, the results remain consistent with our baseline estimation.

[8] Interstate immigration was limited during lockdown periods because of strict border controls.

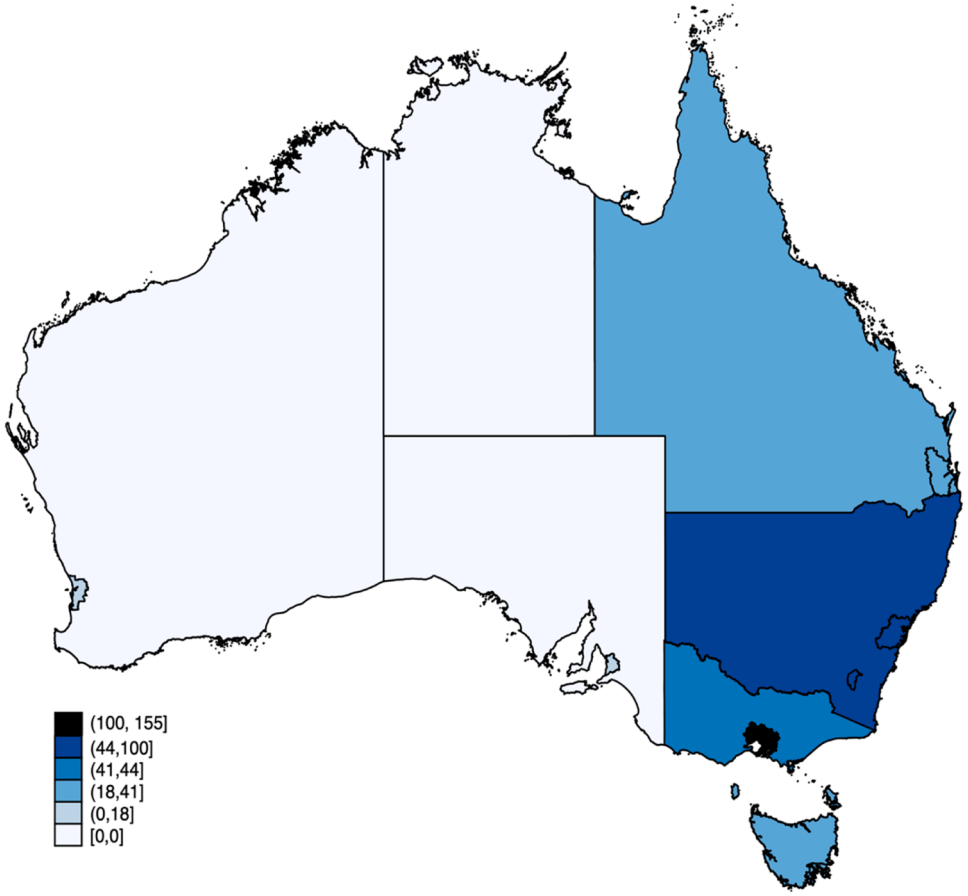

Fig. 2. Maximum lockdown days experienced by HILDA respondents by region.
Source: Maximum lockdown days are obtained by merging lockdown days at the Greater Capital City Statistical Area (GCCSA) and HILDA respondents' interview dates in 2020. Interview date range in 2020 is 3-Aug-2020 to 21-Feb-2021. Treatment definition: Number of lockdown days experienced by the respondent in 2020 up until their interview date.

4.2. Difference-in-differences with a continuous treatment

We estimate the impact of lockdowns on individual loneliness using a continuous treatment DID with individual, region (the Greater Capital City Statistical Area - GCCSA), and year fixed effects:

$$Loneliness_{ist} = t_1 LDD_{ist} + W_{ist} t_2 + \alpha_i + d_t + r_s + n_{ist}, \tag{1}$$

where $Loneliness_{ist}$ is self-reported loneliness for individual i in region s and year t and LDD_{ist} is the number of lockdown days (>7 days) in region s and year t experienced by respondent i. Note that by definition, $LDD=0$ for all respondents in waves 2018 and 2019, and only the treated group has a positive LDD in 2020. Therefore, LDD essentially acts as an interaction term of treatment and treated period. Year fixed effects, d_t, that controls for unobserved time trends across all states and individuals, which also captures before-and-after differences.

We delineate regions at the level of the Greater Capital City Statistical Area (GCCSA), which offers a more granular geographical classification than the state level and distinguishes capital cities from remote areas. We use r_s, region fixed effects that control for region-specific time-invariant characteristics, where effectively include the difference between affected and non-affected regions.[9] α_i further accounts for time-invariant individual-specific characteristics, such as genetic tendencies towards feeling lonely. We also

[9] We also examine region by year fixed effects in section A2.3 of the Appendix, where the number of lockdown days remains statistically insignificant.

conduct the clustered wild bootstrap-t procedure (Cameron et al., 2008) to correct the bias for over-rejection of a null hypothesis from a small number of clusters at the regional level (the number of clusters = 13).[10]

Our interest is t_1, which captures the treatment effect of the lockdown days on individuals' loneliness. To avoid a small coefficient, we scale the *LDD* by multiplying by 0.001. The *LDD* estimate indicates how much loneliness, measured in standard deviations, would change for every 100 days in lockdown.[11]

4.3. Pre-existing trends

We conducted three tests to assess pre-existing differences between affected and non-affected regions. Firstly, we compared pre-treated observables between the treated and control groups, considering demographics, socioeconomics, housing, and social perspectives.

Table 1 presents the results of the pre-COVID balance tests, indicating that most of the observables show no statistical differences. Nonetheless, the following variables demonstrate marginal differences: Affected states tend to have slightly younger populations, showing a difference of 1.2 years, exhibit a slightly lower proportion of immigrants by 3% and a higher proportion of full-time employees by 3%, coupled with a 2% decrease in individuals not participating in the labor force. Affected states also have 4% more individuals with bachelor's degrees or higher education, along with a 4% higher average annual income. In terms of living arrangements, there is a notable difference with 1% more residents living in flats and 6% more living in semi-detached houses compared to their counterparts residing in detached houses. There were no significant differences observed in community participation, such as membership in sports clubs, participation in volunteer or religious activities, engagement in political activities, or charitable donations. Overall, we consider these differences to be relatively small in magnitude. We account for any observed time-variant differences in our estimation and absorb any time-invariant characteristics at the regional or individual level.

Second, we plot average loneliness scores from 2018 to 2020 for states affected by lockdowns and states not affected. Fig. 3 shows that the two groups start with a similar level of average loneliness in 2018, which slightly reduces in 2019—with the treated group reducing by more—before the loneliness level rises in 2020 in the treated group and decreases for the control group. However, the difference between the two groups falls within the 95% confidence interval, and thus there is no evidence of a prior trend. Note that this overall average does not account for observed and unobserved heterogeneity across individuals.

Third, we test whether there is a pre-existing trend in loneliness between the affected and non-affected regions. We estimate the following equation:

$$Loneliness_{ist} = \sum_{t=2018}^{2020} d_t * Treated_s + \sum_{t=2019}^{2020} d_t + X_{ist}\gamma_2 + \alpha_i + e_{ist}, \tag{2}$$

where $\sum_{2019}^{2020} d_t$ is the year fixed effects, using the 2018 control group as the base, and $\sum_{2018}^{t=2020} d_t * Treated_s$ is the interaction term that captures the additional time trend for the affected states after controlling for the overall time trend, d_t. Our hypothesis is that the 2018-treated, 2019-treated, and 2020-treated groups do not differ from those in the 2018 control base.[12] Table 2 presents the results, which show that all interaction terms are not statistically significantly different from the 2018 control region. Fig. 4 further shows the point estimates of interaction terms with 95% confidence intervals, indicating no significant trends between affected and non-affected regions.[13]

4.4. Random assignment of lockdown days

What if the individuals who experienced more lockdown days are intrinsically different from those with fewer days or no lockdowns? We test the number of lockdown days endogenous to individuals' characteristics. We propose the three most 'suspicious' factors that are endogenous to individuals and may induce governments to carry out lockdowns: (1) income, (2) education, and (3) health conditions. In particular, the concern is that a population with a different level of income, education, or health could potentially induce a government to enforce more lockdown days.

Table 3 Panel A shows the regression of these suspicious factors as outcomes on lockdown days. It shows that the treatment variable

[10] According to Abadie et al., (2023), clustering occurs at the level of randomization. The treatment variable, lockdown days, varies at both the regional level (policy level) and the individual level (interview timing). We present the estimates clustered at the regional level, corrected with wild cluster bootstrap. Additionally, we have tested for individual-level clustering, adjusting for instances where the same individual appears multiple times in a panel. The results remain statistically insignificant regardless of the clustering level.

[11] Furthermore, we explore both the intensive margin and extensive margin of days in lockdown using a simple DID with an interaction of two dummies on the full sample, along with a continuous treatment within the treated group. Further details can be found in section A2.4 of the Appendix.

[12] We also conduct pre-existing trend tests using 2018 treated and control groups as the base. The results do not indicate any pre-existing trends and are available upon request.

[13] Due to significant policy changes occurring before 2018, such as the rollout of income management in trialed regions—primarily affecting the control group in our study (Greenacre et al., 2023), which has been linked to a notable decline in socioemotional well-being among welfare recipients (Marston et al., 2020)—we narrow our focus on pre-existing trends to the period between 2018 and 2020.

Table 1
Pre-lockdown summary statistics.

	(1) Treated Mean	SD	(2) Control Mean	SD	(3) Difference Difference	t-stat
Dependent variable						
Loneliness	2.69	1.76	2.71	1.78	0.02	(0.76)
Demographics						
Age	45.98	19.00	47.15	19.27	1.17***	(4.17)
Female	0.53	0.50	0.53	0.50	−0.01	(−0.95)
Married or de facto	0.65	0.48	0.65	0.48	0.00	(0.65)
Separated	0.03	0.16	0.03	0.16	0.00	(0.10)
Divorced	0.06	0.24	0.07	0.25	0.01	(1.78)
Widowed	0.04	0.20	0.04	0.21	0.00	(0.09)
Never married	0.23	0.42	0.21	0.41	−0.01	(−1.91)
Indigenous	0.04	0.19	0.03	0.17	−0.00	(−1.64)
Immigrant	0.20	0.40	0.23	0.42	0.03***	(5.09)
Living alone	0.16	0.36	0.15	0.36	−0.01	(−1.00)
Socioeconomics						
Employed FT	0.43	0.50	0.40	0.49	−0.03***	(−4.30)
EmployedPT	0.21	0.41	0.22	0.42	0.01	(1.06)
Unemployed	0.03	0.18	0.04	0.19	0.00	(1.09)
NotinLabourForce	0.32	0.47	0.34	0.47	0.02**	(3.10)
Bachelor and above	0.29	0.45	0.25	0.43	−0.04***	(−5.85)
Eq HH income	63,285	44,170	60,613	37,949	−2671***	(−4.66)
Dwelling						
Detached	0.80	0.40	0.87	0.34	0.07***	(14.51)
Semi-detached	0.07	0.26	0.06	0.24	−0.01***	(−4.23)
Flat	0.12	0.32	0.06	0.24	−0.06***	(−15.28)
Nursing home	0.00	0.04	0.00	0.04	−0.00	(−0.59)
Other housing	0.01	0.08	0.01	0.08	−0.00	(−0.76)
Social perspectives◆						
Sport club member	0.36	0.48	0.38	0.48	0.01	(1.94)
Volunteer	0.50	0.50	0.51	0.50	0.01	(0.90)
Politically active	0.39	0.49	0.39	0.49	−0.00	(−0.28)
Attending religious service	0.41	0.49	0.39	0.49	−0.02	(−1.67)
Donating to charity	0.88	0.33	0.89	0.32	0.01	(1.24)
Observations (pooled)	24,251		5588		29,839	

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. Loneliness is standardized. The treated group is defined as respondents who live in lockdown states (i.e., in which the number of lockdown days is more than 7): ACT, VIC, NSW, QLD, and TAS. The control group is defined as respondents who live in lockdown-free states (i.e., in which the number of lockdown days is equal to or less than 7): NT and SA, WA. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ◆ Volunteer, politically active, attending religious services and donating to charity are only available in 2018, $N = 11{,}803$ (treated) and 2740 (control).

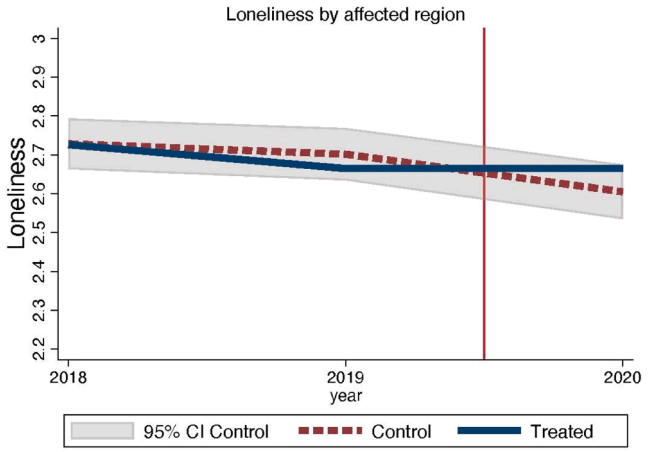

Fig. 3. Loneliness level by year and region affected by lockdown vs not affected.
Note: HILDA 2018–2020 with repeated lockdown measures. The treated group is defined as respondents who live in lockdown states (i.e., in which the number of lockdown days is more than 7): ACT, VIC, NSW, QLD, and TAS. The control group is defined as respondents who live in lockdown-free states (i.e., lockdown days are equal to or less than 7): NT and SA, WA. $N = 17{,}124$.

Table 2
Event study.

VARIABLES	(1) Loneliness
Year 2018* Affected	0.0388
	(0.0450)
Year 2019* Affected	0.000267
	(0.0459)
Year 2020* Affected	0.0271
	(0.0476)
Year 2019	−0.0128
	(0.0240)
Year 2020	−0.0308
	(0.0235)
Observations	42,176
Number of id	15,557
R-squared	0.004
Ind FE	Yes
Ind controls	Yes
Region Year FE	Yes

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. Loneliness is standardized. The treated group is defined as respondents who live in lockdown states (i.e., in which the number of lockdown days is more than 7): ACT, VIC, NSW, QLD, and TAS. The control group is defined as respondents who live in lockdown-free states (i.e., in which lockdown days are equal to or less than 7): NT and SA, WA. Estimates correspond to Eq (2). Standard errors clustered at the regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

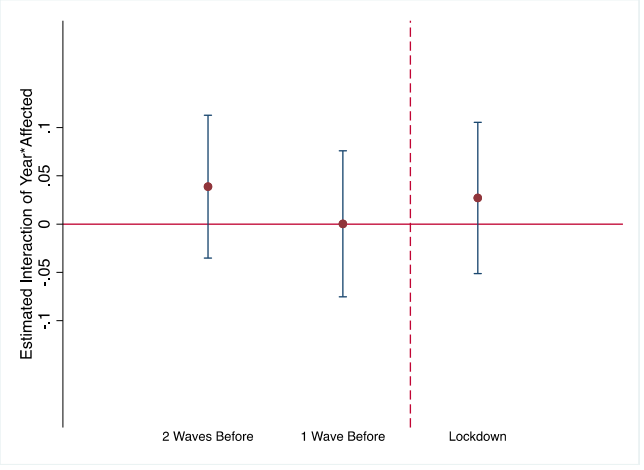

Fig. 4. Event study.
Note: Trend plots and differential changes over time in loneliness between treatment and control groups. Data are from HILDA 2018–2020 with repeated lockdown measures. The figure corresponds to the event study estimated using Eq (2) and results shown in Table 2, and the 2018 control group is used as the base, represented by the omitted dummy variable 2018. Point estimates are the corresponding coefficients of $d_t * Treated_s$. Vertical lines are 95% confidence intervals. Loneliness is standardized. The set of control variables is in Eq (1), including individual-year-region fixed effects. Sample size: 15,557. The figure shows that prior to the introduction of lockdowns, the time trends do not significantly differ between treated and control groups.

is not significantly associated with equivalent household income, highest educational attainment, self-reported general health (1–5), and whether the individual has a chronic illness. This provides further evidence for the quasi-random design, whereby lockdown days until interview days are not endogenous to respondents' characteristics.

To mitigate potential correlations between interview timing and loneliness, we further examine the effects of interview timing by incorporating the following fixed effects into the baseline estimations: (1) interview month fixed effects, (2) interview day of the week

Table 3
Test for random assignment of lockdown days (treatment), and test for interview timing fixed effects.

Panel A VARIABLES	(1) Equivalent hh income	(2) Education>Uni	(4) Self-reported general health (1–5)	(5) Long-term health condition=1
Lockdown days	1614	0.00540	0.0380	−0.0120
	(947.2)	(0.00290)	(0.0149)	(0.0107)
Observations	43,539	43,539	42,043	43,530
R-squared	0.018	0.018	0.003	0.003
Number of id	15,557	15,557	15,555	15,557
Ind FE	Yes	Yes	Yes	Yes
Ind controls	Yes	Yes	Yes	Yes
Region Year FE	Yes	Yes	Yes	Yes

Panel B Interview timing fixed effects	(1) Month	(2) Day of week	(3) Interview date	(4) # Days of fieldwork
Lockdown days	0.0238	0.0204	0.0318	0.0222
	(0.0260)	(0.0261)	(0.0268)	(0.0260)
Observations	42,177	42,177	42,177	42,177
R-squared	0.005	0.005	0.027	0.013
Number of id	15,557	15,557	15,557	15,557
Ind FE	Yes	Yes	Yes	Yes
Ind controls	Yes	Yes	Yes	Yes
Region Year FE	Yes	Yes	Yes	Yes

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. Loneliness is standardized. Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. Panel B includes interview month fixed effects, interview day of the week fixed effects, interview date fixed effects, and the number of days of fieldwork for data collection in each wave, respectively. Standard errors clustered at the regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

fixed effects, (3) interview date fixed effects, and (4) number of days of fieldwork for data collection. Table 3 Panel B displays results consistent with those of the baseline estimation, providing additional evidence that interview timing does not confound the effects of lockdown on loneliness. We will elaborate on the baseline findings in the subsequent discussion.

5. Results

5.1. Baseline with individual fixed effects

Our primary interest is the number of lockdown days (i.e., t_1 in the baseline model). If it is significant and positive, this indicates that the number of lockdown days increases the loneliness level. Note that individual fixed effects estimates compare loneliness within the same individual before and after the lockdown. Table 4, column 1 presents lockdown estimates without individual controls (note that the treated dummy is eliminated by individual fixed effects), and the lockdown effect is small and positive but not statistically significant. After adding individual characteristics in column 2, and region and year fixed effects in column 3, the estimate of lockdown does not change materially. The point estimate suggests that for a 100-day lockdown, the loneliness level increases by 1% to 2% of a SD.

To provide more context for the effect size, we first benchmark this magnitude to being widowed (using married as the base) and find that widowhood increases loneliness by 48.2% - 49.2% of a SD. Second, we conduct a falsification test that uses our baseline model to estimate other factors in economic well-being: financial stress and mental health. Previously, studies have found that lockdowns increase financial stress (Adegboye et al., 2021) and decrease mental health (Butterworth et al., 2022). Table 5 shows that our identification captures 4.2% of a SD increase in financial stress significantly and 12.8% of a SD decrease in mental health significantly. Compared with these two benchmarks, we show the effect of lockdown on loneliness is thus statistically and empirically insignificant.

5.2. Test for non-linear lockdown effect

The baseline model assumes that the number of lockdown days and loneliness have a linear relationship. We test if loneliness is significantly affected by different thresholds of lockdown days, where we break down the number of lockdown days by quartiles and represent these quartiles using dummy variables. LDD in Eq (1) is replaced by these quartiles,[14] and the results from this re-estimated model are presented in Table 6. We find that, relative to the bottom quartile, the 2nd-4th quartiles do not have significantly different effects on loneliness.

[14] The first quartile incorporates lockdown durations of fewer than 33 days, the second quartile includes durations less than 43 days, and the third quartile consists of durations fewer than 48 days.

Table 4
Baseline difference-in-differences estimates with three-way fixed effects.

VARIABLES	(1) Loneliness	(2) Loneliness	(3) Loneliness
Lockdown days	0.0139	0.0136	0.0211
	(0.0313)	(0.0321)	(0.0191)
	$p = 0.314$	$p = 0.342$	$p = 0.330$
Widowed		0.482**	0.492**
		(0.0901)	(0.106)
		$p = 0.00$	$p = 0.00$
Observations	43,815	43,787	43,787
R-squared	0.000	0.003	0.004
Number of id	17,180	17,168	17,168
Ind FE	Yes	Yes	Yes
Ind controls	No	Yes	Yes
Region Year FE	No	No	Yes

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. Loneliness is standardized. Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. Standard errors clustered at the regional level are in parentheses. p-values of wild-t are calculated using the wild bootstrap-*t* procedure. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
Falsification tests.

VARIABLES	(1) Financial stress	(2) Mental health
Lockdown days	0.0416*	−0.128**
	(0.0126)	(0.0218)
Observations	41,025	41,275
R-squared	0.011	0.014
Number of id	15,522	15,535

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. Financial stress is generated by principal component analysis that includes 7 questions regarding financial hardship and cash flow problems. Mental health is from the SF36 Mental Component Summary using factor analysis of 8 SF36 factors. Outcomes are standardized for easy comparison. Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. Standard errors clustered at the regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6
Test for discreet measures of lockdown days.

VARIABLES	(1) Loneliness	(2) Loneliness	(3) Loneliness
LDD_2ndQuartile	0.0155	0.0141	0.00624
	(0.0207)	(0.0209)	(0.0274)
LDD_3rdQuartile	−0.00614	−0.00760	−0.0151
	(0.00733)	(0.00787)	(0.0203)
LDD_4thQuartile	0.000386	0.00184	−0.00639
	(0.00104)	(0.00222)	(0.0188)
Observations	43,164	43,140	43,140
R-squared	0.000	0.003	0.004
Number of id	16,529	16,520	16,520
Ind FE	Yes	Yes	Yes
Ind controls	No	Yes	Yes
Year FE	No	No	Yes

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. Lockdown days range from 0 to 154 days, and quartile dummies are used (bottom quartile is the base). Loneliness is standardized. Standard errors clustered at the regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3. Concurrent effect

Our baseline estimation uses the cumulative days of lockdown experienced by an individual. We also examine whether the concurrent effect of lockdown affects loneliness—that is, whether people who are in lockdown when interviewed report higher levels of loneliness. In the sample, 18% of respondents in 2020 were interviewed during lockdown (2293 in Melbourne and 9 in other regions). For this subsection only, we redefine the treatment variable as currently in lockdown=1 and 0 otherwise, and re-estimate the baseline estimation. The results are presented in Table 7 Panel A, which shows that being in lockdown does not significantly increase loneliness. In the Appendix, we also add both *inlockdown* dummy and the number of lockdown days experienced up until the interview in one regression. We find that both variables are statistically insignificant (see Table A6).

Given that Greater Melbourne is the only region that experienced a significant lockdown period during the interview date range, we further plot the loneliness level in Melbourne after 1 month of lockdown (the earliest point the interview date can capture), 2 months of lockdown, the end of lockdown, 1 month out of lockdown, and 2 months out of lockdown. Fig. 5 shows that there are barely any changes in loneliness at different time points for lockdown and that 95% confidence intervals are within the all-time average and within 1 SD range of the all-time average.[15] This result shows that there are no significant during or after effects, and we do not have evidence that loneliness would have undergone transitory change in response to lockdown events. This finding aligns with those of Mund et al. (2020), who show that loneliness exhibits traits-like stability over time.

5.4. External validity

The Melbourne sample also enables us to test if loneliness is anchored by peer effects. One concern about using COVID lockdowns as a natural experiment is that people who are in lockdown may compare their situation with their peers' experiences. Since lockdowns usually impact a whole region, having peers also in lockdown could contribute to their mental adjustment, making them less likely to feel lonely. We test if these peer effects threaten the external validity of this natural experiment by conducting spatial analysis that accounts for the distance between residential address and the Melbourne city border for Melbourne residents. This test relies on the assumption that people who live near the borders of Melbourne are more likely to have a social network that is not in lockdown. If peer effects confound the natural experiment, we would anticipate that the distance to the border during lockdown would significantly contribute to feelings of loneliness.

The HILDA restricted release contains respondent's geographic location at the Statistical Areas Level 1 (SA1) level, with an average population of 400 people (Australia Bureau of Statistics). We present Fig. 6, where dark green indicates SA1 surveyed in Melbourne, light green indicates the rest of Melbourne, and yellow indicates the rest of Victoria state. This shows that HILDA covers a wide range of SA1 across Melbourne, including many border respondents. The average distance to the city border is 37.8 km (SD = 9.3 km), which we calculate using the STATA command *geonear*. We estimate the spatial difference-in-differences model:

$$Loneliness_{iast} = \delta_1 inlockdown_{ist} * Dist_{ia} + \delta_2 inlockdown_{ist} + \delta_3 Dist_{ia} + \ W_{ist}t_2 + \alpha_i + d_t + r_s + n_{ist} \tag{3}$$

where $Dist_{ia}$ captures the nearest distance of respondent i living in area a of the SA1 to the Melbourne border. $inlockdown_{ist}$=1 if the respondent is in lockdown during the interview, 0 otherwise. The interaction term $inlockdown_{ist} * Dist_{ia}$ is the additional spatial effect during lockdowns. We control for the same variables as in the baseline estimation.

Table 7 Panel B presents the estimation results, where Distance to Melbourne border is significantly positive, suggesting people who are living further from the border (i.e., close to Melbourne CBD) are more likely to feel lonely. However, there is no significant effect of lockdown, and no significant treatment effect from distance. This exercise provides evidence that peer effects are not key contributors to the non-significant results.

Another potential challenge to external validity arises from the concern that lockdowns might universally enhance people's sense of community. To delve deeper into this, we undertake two tests: (1) examining whether lockdowns correlate with an increase in community satisfaction (scaled from 0 to 10, mean=6.76, SD=2.18) ;[16] and (2) assessing whether controlling for community satisfaction would alter the significance of the lockdown estimate on loneliness. The results, as depicted in Table 7 Panel C, indicate no statistically significant impact of lockdowns on community satisfaction. Furthermore, the second column reveals that community satisfaction mitigates loneliness levels, yet it does not alter the statistical significance of the lockdown's effect on loneliness. In other words, we find no evidence suggesting that community satisfaction poses an external threat, thus affirming the validity of employing COVID lockdowns as a natural experiment to assess physical isolation.

5.5. Exclusion restrictions

In this subsection we investigate if lockdown impacts factors other than physical isolation and, in turn, affects loneliness. We

[15] Note that in 2020, data collection was expedited compared to previous years, owing to the implementation of telephone interviews, which eliminated travel time. As a result, there are fewer observations in the later months of the survey. However, any potential effects arising from this change will be offset by the difference-in-differences setup, as it affects both the treated and control groups uniformly.

[16] Given that the majority of lockdowns in Australia occur at localized geographic levels, primarily at the suburb or city levels (refer to Appendix Table A1), and infrequently at the national level, we employ a community-level measure to investigate the "unity effect."

Table 7
Concurrent effect and External validity of COVID lockdown: (1) spatial analysis of Melbourne sample, (2) community satisfaction.

Panel A VARIABLES	(1) Loneliness	(2) Loneliness	(3) Loneliness
inlockdown = 1	−0.00316	−0.00167	−0.00620
	(0.00896)	(0.0106)	(0.0143)
Observations	42,198	42,176	42,176
R-squared	0.000	0.003	0.004
Number of id	15,563	15,557	15,557
Panel B VARIABLES	**(1) Loneliness**	**(2) Loneliness**	**(3) Loneliness**
inlockdown* km_to_border	−0.000257	−0.000207	−0.000191
	(0.00188)	(0.00189)	(0.00189)
inlockdown = 1	0.00816	0.000226	−0.143
	(0.0741)	(0.0744)	(0.132)
km_to_border	0.0120*	0.0137**	0.0134**
	(0.00678)	(0.00681)	(0.00681)
Observations	7739	7738	7738
R-squared	0.001	0.007	0.007
Number of id	3023	3022	3022
Ind FE	Yes	Yes	Yes
Ind controls	No	Yes	Yes
Year FE	No	No	Yes
Panel C VARIABLES	**(1) Community Satisfaction**		**(2) Loneliness**
Lockdown days	0.0877		0.152
	(0.208)		(0.109)
Community satisfaction			−0.0208***
			(0.00343)
Observations	49,093		44,564
R-squared	0.006		0.007
Number of id	18,962		18,031

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. Loneliness is standardized. In lockdown=1 if an individual is in lockdown at the time of interview, 0 otherwise. Panel A: In our sample, 18% of individuals in 2020 were interviewed during lockdown (mainly in Melbourne). Panel B: dist is the distance of Melbourne residents to the Melbourne border (i.e. not in lockdown) in km. Panel C: Community satisfaction is scaled from 0 to 10. Lockdown days are defined as the baseline estimation. estimations control for individual characteristics, individual fixed effects and region and year fixed effects. $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

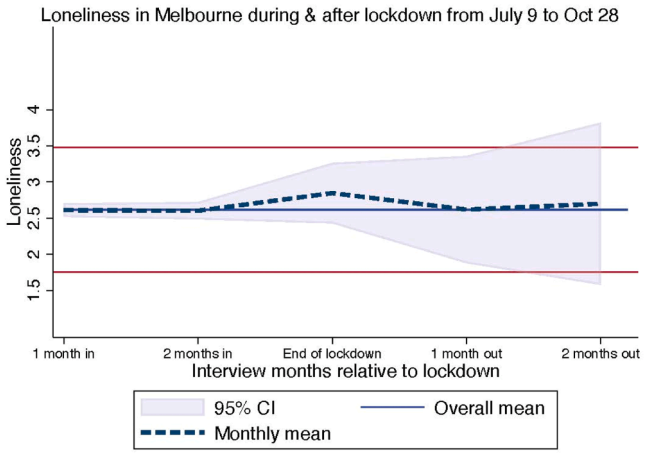

Fig. 5. During and after lockdown and loneliness.
Note: HILDA 2020 Melbourne sample. This uses the second lockdown in Melbourne from 09/07/2020 to 28/10/2020. HILDA interviews start on 3-Aug-2020, which capture as early as 1 month after the commencement of the second lockdown in Melbourne. $N = 2293$.

Fig-

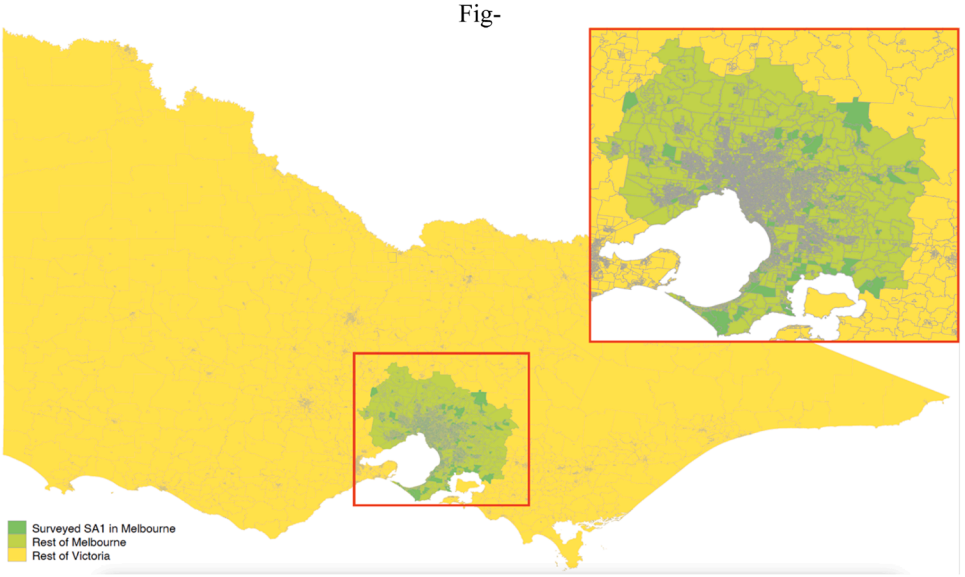

Fig. 6. Melbourne SA1 regions surveyed by HILDA.
Note: Figure is generated by merging HILDA SA1 regions with ABS Victoria SA1 geopackage.

separately test the following aspects by adding each to the baseline estimation:

1. Social channel. (a) Get together with friends: '*How often do you get together socially with friends/relatives not living with you?*' (1=*Every day* to 7=*Less often than once every 3 months*) (reverse coded; mean = 4.3, SD = 1.5), (b) has access to the internet at home=1 (mean = 0.87, SD = 0.9).
2. Work channel. (a) Working from home=1 (mean = 0.18, SD = 0.39), (b) ANZSIC job industry (2-digit classification).
3. Household channel. (a) Type of dwelling (apartment, house, or townhouse), and (b) household composition (couple, with children, with others, or alone).
4. Health channel. (a) Individual health (using the 36-Item Short Form Health Survey—i.e., the SF-36, which ranges from 0 to 100, mean = 66.2, SD = 20.9), (b) have had COVID-19 (mean = 0.005, SD = 0.076 in year 2020).
5. COVID-19 cases and macroeconomic channel. (a) COVID-19 cases, (b) COVID-19 deaths, (c) COVID-19 cases in aged care services (both among residential care and in-home care) by states in 2020 from the Department of Health, (d) total gross income per capita in AUD, population at state-year level.

Table 8 presents the results, and shows that these confounders do not change the statistically insignificant effects of lockdown. These results not only illuminate the exclusion restriction, offering additional evidence of the quasi-experimental nature of the lockdown's impact on physical isolation but also deepen our understanding of physical isolation and social connectedness. We discovered that engaging in social activities, such as spending time with friends and relatives, significantly reduces levels of loneliness (coefficient = −0.0474, p-value < 0.01). Importantly, the inclusion of social interaction does not alter the impact of physical isolation on loneliness in terms of statistical significance and effect size. This implies that social interaction and physical isolation are independent factors when it comes to their influence on loneliness.

6. Further results

6.1. Heterogeneous effect

We subsequently investigate whether the lockdown affects distinct demographic and socioeconomic subgroups independently, in line with prior literature suggesting variations in loneliness based on individual characteristics (Cohen-Mansfield et al., 2016; de Jong Gierveld et al., 2015). To assess heterogeneous treatment effects, we specifically examine the following factors: (1) living arrangements, (2) remoteness, (3) personality, (4) income, (5) age, (6) immigrant status, and (7) indigenous status. Furthermore, we explore whether there is a differential effect when individuals perceive the lockdown more acutely during weekends.[17]

Table 9 presents the DID lockdown effects across these subgroups, revealing predominantly statistically insignificant results across most regressions. While point estimates vary among subgroups, the overall effect size remains small, and the lack of significance

[17] Since data collection fieldwork is not conducted during major holidays, we are unable to estimate the heterogeneous effects of holidays.

Table 8
Exclusion restrictions.

Panel A: Household			Panel B: Health	
	(1)	(2)	(1)	(2)
Lockdown days	0.0205	0.0212	0.0277	0.0211
	(0.0143)	(0.0154)	(0.0138)	(0.0142)
Observations	42,175	42,176	41,862	42,173
R-squared	0.005	0.006	0.017	0.004
Number of id	15,557	15,557	15,554	15,557
Dwelling	Yes			
HH composition		Yes		
Have COVID			Yes	
General health				Yes
Panel C: Work			**Panel D: Social**	
	(1)	(2)	(1)	(2)
Lockdown days	0.0226	−0.0187	−0.00578	0.0209
	(0.0196)	(0.0211)	(0.0259)	(0.0186)
Observations	42,170	26,258	41,738	42,168
R-squared	0.004	0.011	0.009	0.004
Number of id	15,557	10,817	15,549	15,557
WFH	Yes			
Job industry		Yes		
Social			Yes	
Internet				Yes

Panel E: COVID & Macro					
	(1)	(2)	(3)	(4)	(5)
Lockdown days	0.0441	0.0355	0.0331	0.0275	0.0197
	(0.0482)	(0.0390)	(0.0377)	(0.0200)	(0.0189)
Observations	42,176	42,176	42,176	42,176	42,176
R-squared	0.004	0.004	0.004	0.004	0.004
Covid cases	Yes			15,557	15,557
Covid deaths		Yes			
Covid in aged care			Yes		
Population				Yes	
Income per capita					Yes

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. The following controls are added, respectively: Type of dwelling (apartment, house, or townhouse); Household composition (couple, with children, with others, or alone); Individual health (SF36); Have had COVID; Working from home=1 (mean=0.18, SD=0.39); ANZSIC job industry (2-digit classification); "*How often do you get together socially with friends/relatives not living with you?*" (1=*Every day* to 7=*Less often than once every 3 months*) (reverse coded; mean = 4.3, SD = 1.5); Has access to the internet at home= 1 (mean = 0.87, SD = 0.9). Statistics on COVID-19 cases, COVID-19 deaths, and COVID-19 cases in aged care services (both residential care and in-home care) by states in 2020 from the Department of Health. Total gross income per capita and population at state-year level are obtained from the Australian Bureau of Statistics. Loneliness is standardized. Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. Standard errors clustered at the regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

provides additional evidence that loneliness is unaffected by physical isolation across demographic and socioeconomic groups. Moreover, we find no evidence of differential effects during weekends.

Two exceptions arise regarding extroverted individuals and young people aged 15–25 years old. The findings suggest that a 100-day lockdown results in a 6% increase in loneliness among extroverted individuals and a 33.6% increase among young people, as measured in standard deviation units. Both of these findings are statistically significant at the 10% level. This suggests that both young people and those with extroverted tendencies may face a heightened risk of experiencing loneliness in response to physical isolation, aligning with prior research findings on the impacts of COVID lockdown measures (e.g., Bu et al., 2020; Entringer and Gosling, 2022; Hu and Gutman, 2021; Sampogna et al., 2021).

6.2. Mechanism

Next, we explore the mechanism of which people respond to lockdowns that could alleviate the effect of physical isolation. We examine the time use data in HILDA, and find that lockdowns are associated with less time in commuting and running errands, and more time in doing housework and playing with children (see Table 10). We also show that relationship satisfaction towards partner increased during lockdowns, which supports the findings of Hamermesh (2020) who shows negative effects of lockdowns are mediated by increased time spent together as couples.

Table 9
Heterogeneous effects.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lockdown days	0.0173	0.0129	0.0183	0.0272	0.336*	−0.0168	0.0499	0.188	0.0131
	(0.0157)	(0.0417)	(0.0157)	(0.0158)	(0.0836)	(0.0156)	(0.0224)	(0.229)	(0.0270)
Living alone * Lockdown days	0.0302								
	(0.0337)								
Major city * Lockdown days		0.00824							
		(0.0423)							
Low income * Lockdown days			0.00865						
			(0.0196)						
Male * Lockdown days				−0.0135					
				(0.0205)					
Age 26–65 * Lockdown days					−0.365*				
					(0.0922)				
Age 65 above * Lockdown days					−0.368*				
					(0.0881)				
Extroverted * Lockdown days						0.0619*			
						(0.0174)			
English speaking.Immi * Lockdown days							−0.105		
							(0.0642)		
Non-English speaking.Immi i * Lockdown days							−0.129		
							(0.0499)		
Indigenous * Lockdown days								−0.168	
								(0.230)	
Weekend * Lockdown days									0.0488
									(0.0439)
Observations	42,176	42,161	42,176	42,176	42,176	38,321	42,170	42,151	42,177
R-squared	0.005	0.004	0.004	0.004	0.007	0.005	0.005	0.004	0.004
Number of id	15,557	15,557	15,557	15,557	15,557	13,938	15,555	15,546	15,557

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. Dependent variable is standardized loneliness at the individual level. Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. It interacts with the following dummy variables: living alone, living in a major city, household income is below the median, age group (15–25, 26–65, and 65 and above), male, extroverted (more than median in the extroversion-introversion scale), immigrant (from an English or non-English-speaking country), and indigenous status, respectively. Standard errors clustered at the regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10
Lockdown Mechanism.

VARIABLES	(1) Relationship satisfaction	(2) Commute	(3) Errands	(4) Housework	(5) Play with child
Lockdown days	0.0814***	−0.708***	−0.215**	0.384***	0.571**
	(0.0113)	(0.0774)	(0.0960)	(0.0946)	(0.266)
Observations	31,070	41,395	42,008	42,458	40,752
R-squared	0.017	0.069	0.006	0.009	0.019
Number of id	12,450	16,359	16,397	16,426	16,298

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. Dependent variables are defined as follows (1) Satisfaction with partner (0, Completely dissatisfied, to 10, Completely satisfied, (2) Travelling to/from paid employment (hrs/week); (3) household errands (hrs/week); (4) housework (hrs/week); and (5) Playing with your children (hrs/week). Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. All regressions control for individual characteristics with individual, year, and region fixed effects. Standard errors clustered at the regional level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.3. Other robustness checks

We test whether already lonely people are more likely to have a higher treatment effect of lockdowns. We conduct quantile regression, and find that per 100-day lockdown change the conditional distribution of loneliness from −0.006 in the bottom decile, to 0.05 in the top decile, holding other covariates constant, and all estimates remain statistically insignificant (see Table 11 Panel A).

We conduct sensitivity analysis (1) using raw lockdown days; (2) limiting the sample to living alone, not having moved during the study period, and living in a major city, respectively; and (3) including the 10 previous waves (i.e., to 2010). The results are

Table 11
Further results. Panel A: Quantile regression. Panel B: Sensitivity test. Panel C: Attrition Test.

Panel A					
Quantile regression	(1)	(2)	(3)	(4)	(5)
VARIABLES	Quantile=0.1	Quantile=0.25	Quantile=0.5	Quantile=0.75	Quantile=0.9
Lockdown days	−0.00648	0.00241	0.0195	0.0420	0.0523
	(0.146)	(0.111)	(0.145)	(0.292)	(0.366)
Observations	42,176	42,176	42,176	42,176	42,176
Ind FE	Yes	Yes	Yes	Yes	Yes
Ind controls	Yes	Yes	Yes	Yes	Yes
Region Year FE	Yes	Yes	Yes	Yes	Yes

Panel B					
Sensitivity	(1)	(2)	(3)	(4)	(5)
VARIABLES	Raw LDD	Living alone	Not moved sample	Major city	Sample 2010–2020
Lockdown days	0.000222	0.0499	0.0281	0.0202	0.0425
	(0.000195)	(0.0297)	(0.0200)	(0.0264)	(0.0230)
Observations	42,176	6551	40,408	27,914	107,450
R-squared	0.004	0.007	0.003	0.005	0.010
Number of id	15,557	2804	14,778	10,423	15,153
Ind FE	Yes	Yes	Yes	Yes	Yes
Ind controls	Yes	Yes	Yes	Yes	Yes
Region year FE	Yes	Yes	Yes	Yes	Yes

Panel C			
Attrition test	(1)	(2)	(3)
VARIABLES	SCQ longitudinal weight	Responding person longitudinal weight	Inverse probability weight
Lockdown days	0.0243	0.0165	0.0225
	(0.00984)	(0.0114)	(0.0183)
Observations	37,020	39,366	35,147
R-squared	0.005	0.005	0.005
Number of id	13,028	14,201	15,385

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. All regressions control for time-variant personal characteristics, and individual-year-regional fixed effects. Panel A uses quantile regression with individual fixed effects. Panel B tests raw lockdown days (instead of days more than 7), multiplying by 0.01; samples of living alone, not moved, major cities, and using HILDA 2010–2020 waves. Panel C uses self-completed questionnaire longitudinal weight, responding person longitudinal weight, and inverse probability weight, where we calculate the probability of staying in the next wave based on current wave characteristics and inverse the probability to inflate the sample and make up for those who are more likely to drop out. There was a dramatic change in the mode of data collection, from face-to-face to phone interviews in wave 20. However, this did not make a dramatic impact on the response rate. According to a technical report, the response rate for previous wave respondents was still 95.6% in the main sample of HILDA, attributed to the fact that the fieldwork company had at least one phone number for 99.4% of the respondents. According to the report, the wave 20 response rate was also close to that achieved in previous two waves for Melbourne, the area most affected by lockdowns (Watson, Jin, and Summerfield 2021). Loneliness is standardized. Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. Standard errors clustered at the regional level are in parentheses. p-values of wild-t are calculated using the wild bootstrap-*t* procedure. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

consistently statistically insignificant throughout (see Table 11 Panel B)

Last, we conduct an attrition test by using a self-completed questionnaire longitudinal weight, respondent's longitudinal weight, and inverse probability weight and find that results are statistically insignificant across weighted estimations (see Table 11 Panel C).[18]

7. Conclusion

Loneliness has garnered increased attention in recent years, particularly since the onset of the COVID-19 pandemic. To investigate the relationship between loneliness and lockdown measures, we turn to the case of Australia, where stringent stay-at-home orders were imposed. Leveraging ongoing panel survey data containing information on residential location and loneliness, we analyze if variations in the duration of lockdowns at the regional and individual level contribute to feelings of loneliness. Utilizing a national representative longitudinal dataset with loneliness measures dating back to 2001, we use DID and adjust for individual characteristics, and unobserved individual, region and year heterogeneity that may influence this relationship. Our findings indicate that being in lockdown, as

[18] Despite the transition from face-to-face to telephone interviews, the response rate has remained consistently high, surpassing 95%. This outcome can be attributed to a series of quality control measures and adjustments made to the incentive scheme—see Watson et al. (2021), for an in-depth analysis of the COVID-related impacts on HILDA data collection.

well as the duration of lockdown, are not associated with reported levels of loneliness. Moreover, our results suggest that physical isolation and loneliness are distinct constructs. While the notion of "being alone" is often conflated with being lonely, our study highlights their uniqueness.

Despite its contributions to the literature, our study has limitations. Specifically, our findings may not be generalizable to other countries. For instance, Australians have relatively advanced means of telecommunication, and our results may not hold true for countries where access to communication without in-person contact is limited. Therefore, future research that examines the impact of lockdowns and physical isolation on loneliness in diverse contexts would be beneficial.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Chat GPT in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The author declares that she has no relevant or material financial interests that relate to the research described in this paper.

Data availability

The authors do not have permission to share data.

Appendix

A1. Information sources to calculate lockdown days

The search words utilized in the search included, “lockdown”, “restriction”, “stay-at-home”, “stage three”, “stage four” and “essential reason”. The initial Google search produced 14 bouts of lockdowns in the January 2020 to February 2021 period to be considered across the States. These 14 bouts of lockdown were then checked against each State Governments’ media releases over the January 2020 to February 2021 period to determine the details of each bout of lockdown and ensure that the bouts included legislation that enforced leaving homes for activities that only fell under four essential categories. These State media release archives included ACT Government media releases (https://www.cmtedd.act.gov.au/open_government/inform/act_government_media_releases), NSW Government Ministerial media releases (https://www.nsw.gov.au/media-releases), Northern Territory Government newsroom (https://newsroom.nt.gov.au/), the Queensland Cabinet and Ministerial Directory (https://statements.qld.gov.au/), Government of South Australia: COVID-19 latest news (https://www.covid-19.sa.gov.au/latest-news), Tasmania Government COVID-19 updates (https://www.premier.tas.gov.au/covid-19_updates), Premier of Victoria media center (https://www.premier.vic.gov.au/media-center) and Government of Western Australia media statements (https://www.mediastatements.wa.gov.au/). Legislative directions, as well as the Department of Health and police services’ media releases were also utilized. These sources provided a detailed account of the freedom individuals lost or gained, as well as the exact date and time individuals were imposed or lifted. This subsequent search of State Government media releases, utilizing the same search terms, refined the details of each lockdown and excluded four bouts of lockdowns, three in the Northern Territory, South Australia and Western Australia in the March 2020 to May 2020 period and one in Queensland in the August 2020 to October 2020 period. This was due to these bouts of lockdown falling outside the criteria for inclusion as they did not include the legislatively enforced ‘four essential categories’ to leave homes. This left 10 bouts of lockdowns to be included for the January 2020 to February 2021 period: one bout for the Australian Capital Territory, two within New South Wales, zero in the Northern Territory, two within Queensland, one within South Australia, one in Tasmania and three bouts of lockdown in Victoria. Bouts of lockdown lasted as little as three days, to as long as 112 days, however the mean of all lockdowns was 33.1 days.

Table A1
Lockdown days by region in the Period of 01/01/2020- 17/02/2021.

		First lockdown	Second lockdown	Third lockdown
ACT		Begun: 29/03/2020 Ended: 09/05/2020 **(41)**		
NSW	Greater Sydney	Begun: 31/03/2020 Ended: 15/05/2020 **(45)**		
	Regional	Begun: 31/03/2020 Ended: 15/05/2020 **(45)**	Begun: 19/12/2020 Ended: 09/01/2021 **(21)** [Northern Beaches LGA]	
NT				
QLD	Greater Brisbane	Begun: 30/03/2020 Ended: 02/05/2020 **(33)**	Begun: 08/01/2021 Ended: 11/01/2021 **(3)**	

(*continued on next page*)

Table A1 (*continued*)

		First lockdown	Second lockdown	Third lockdown
	Regional	Begun: 30/03/2020 Ended: 02/05/2020 **(33)**		
SA	Greater Adelaide	Begun: 19/11/2020 Ended: 22/11/2020 **(3)**		
	Regional			
TAS		Begun: 31/03/2020 Ended: 11/05/2020 **(41)**		
VIC	Greater Melbourne	Begun: 31/03/2020 Ended: 13/05/2020 **(43)**	Begun: 09/07/2020 Ended: 28/10/2020 **(111)**	Begun: 12/02/2021 Ended: 18/02/2021 **(5)**
	Regional	Begun: 31/03/2020 Ended: 13/05/2020 **(43)**	Begun: 12/02/2021 Ended: 18/02/2021 **(5)**	
WA	Greater Perth	Begun: 31/01/2021 Ended: 05/02/2021 **(5)**		
	Regional	Begun: 31/01/2021 Ended: 05/02/2021 **(5)** [Peel & South-West regions]		

Sources: Various State Governments' media releases and statements.

A2. Additional robustness checks

A2.1 Without ACT, NT and TAS

We conduct a robustness analysis by testing samples that exclude the Australian Capital Territory (ACT) and Northern Territory (NT). This examination aims to address concerns regarding the unique characteristics of NT, which features a significantly more rural landscape and a higher proportion of indigenous population compared to the rest of Australia; and ACT represents a more urbanized, high-income region. Additionally, we test the exclusion of Tasmania (TAS), an island state with a much smaller and more dispersed population compared to the other states. To handle the limited number of clusters (11 regions without ACT and NT, and 10 without TAS), we employ the wild cluster bootstrap method. The results shown in Table A2 closely align with the baseline estimation, indicating robustness across different sample compositions.

Table A2
Test sample excluding potential outlier states/territories.

VARIABLES	(1) Exclude ACT & NT	(2) Exclude AC, NT & TAS
Lockdown days	0.0209	0.0200
	(0.0183)	(0.0198)
	[$p = 0.354$]	[$p = 0.402$]
Observations	40,032	38,614
Number of id	14,724	0.004
R-squared	0.004	14,203
Ind FE	Yes	Yes
Ind controls	Yes	Yes
Region Year FE	Yes	Yes

Note: HILDA waves 2018–2020. Sample is limited to those who have repeated loneliness measures. All regressions control for time-variant personal characteristics, and individual-year-regional fixed effects. Loneliness is standardized. Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. Standard errors clustered at the regional level are in parentheses. p-values of wild-t are calculated using the wild bootstrap-*t* procedure. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A2.2 Ordered logit regression and average marginal effects

As a supplement to the standardized loneliness measure, we also employ ordered logit regression using the raw Likert scale for baseline estimation. Additionally, concerns may arise that linear regressions do not adequately capture distributional changes above the average. Therefore, we present the average marginal effects across responses ranging from 1 to 7 points. The ordered logit results presented in Table A3, Panel A, demonstrate no significant deviations from our baseline findings. Moreover, we find estimates across 7 responses remain small in magnitude and statistically insignificant, suggesting no evidence of significant changes beyond the average (see Panel B). These results further reinforce the notion that the estimated impact of lockdown on loneliness is minimal and statistically insignificant, aligning closely with our primary findings.

Table A3
Ordered logit regression with individual fixed effects and average marginal effects.

Panel A	(1)	(2)	(3)
VARIABLES	Loneliness	Loneliness	Loneliness
Lockdown days	0.0466	0.042	0.0715
	(0.0352)	(0.132)	(0.0844)
Observations	63,540	63,504	63,504
Ind FE	Yes	Yes	Yes
Ind controls	No	Yes	Yes
Region Year FE	No	No	Yes

Panel B	I often feel very lonely						
	1: strongly disagree	2	3	4	5	6	7: strongly agree
Average marginal effect	−0.0128	−0.0057	0.0013	0.0047	0.0050	0.0044	0.0030
	(0.0153)	(0.0068)	(0.0016)	(0.0057)	(0.0059)	(0.0053)	(0.0036)

Note: HILDA waves 2018–2019. Sample is limited to those who have repeated loneliness measures. Loneliness measure is 1 to 7 on *How much do you agree or disagree: I often feel very lonely,* where 1 is for *strongly disagree* and 7 is for *strongly agree.* Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. The treated group is defined as respondents who live in lockdown states (i.e., in which the number of lockdown days is more than 7): ACT, VIC, NSW, QLD, and TAS. The control group is defined as respondents who live in lockdown-free states (i.e., in which lockdown days are equal to or less than 7): NT and SA, WA. Panel A presents fixed effects ordered logistic regression, same as the baseline specification. Panel B presents average marginal effects of lockdown by across responses ranging from 1 to 7 points of loneliness questions. The effects are calculated based on the third column in Panel A. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A2.3 Region by year fixed effects

In addition to the aforementioned regional, year, and individual fixed effects, which absorb time-invariant regional differences, personal-level disparities, and common time trends, we further examine region-by-year fixed effects. By incorporating region-by-year fixed effects, we account for any region-specific time trends within the model. This adjustment helps address potential variations in region-specific trends related to different trajectories of loneliness levels. Such variations may stem from changes in demographic profiles, infrastructural factors such as housing and community facilities, as well as political distinctions. As illustrated in Table A4, the effect of lockdown on loneliness remains statistically significant, consistent with our primary findings.

Table A4
Regional by year fixed effects.

VARIABLES	(1) Loneliness
Lockdown days	0.154
	(0.108)
Observations	42,177
Number of id	15,557
R-squared	0.006
Ind FE	Yes
Ind controls	Yes
Region by Year FE	Yes

Note: HILDA waves 2018–2019. Sample is limited to those who have repeated loneliness measures. Loneliness measure is 1 to 7 on *How much do you agree or disagree: I often feel very lonely,* where 1 is for *strongly disagree* and 7 is for *strongly agree.* Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. The treated group is defined as respondents who live in lockdown states (i.e., in which the number of lockdown days is more than 7): ACT, VIC, NSW, QLD, and TAS. The control group is defined as respondents who live in lockdown-free states (i.e., in which lockdown days are equal to or less than 7): NT and SA, WA. The estimation controls for marital status, labor

market status, education level and region by year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A2.4 Intensive margin and extensive margin

Furthermore, we conduct an analysis of the intensive margin and extensive margin of days in lockdown. We employ a two-dummy-interaction difference-in-difference approach (*Treated*After*) by comparing the affected region before and after lockdown to obtain the extensive margin. Additionally, we estimate lockdown days as a treatment variable within the treated group for the intensive margin. The results are presented in Table A5, and both indicate insignificant treatment effects. This finding suggests that loneliness is not primarily driven by either the broad spectrum of lockdown experiences or the more intense and prolonged periods of lockdown. This nuanced insight underscores the robustness of the findings, as neither the extensive nor the intensive margin emerges as a dominant driver of the observed effects on loneliness.

Table A5
Intensive margin and extensive margin.

VARIABLES	(1) Extensive margin	(2) Intensive margin
Treated*After	0.143	
	(0.170)	
Lockdown days		0.155
		(0.109)
Observations	42,173	34,261
R-squared	0.006	0.006
Number of id	15,554	12,679

Note: HILDA waves 2018–2019. Sample is limited to those who have repeated loneliness measures. Loneliness measure is 1 to 7 on *How much do you agree or disagree: I often feel very lonely,* where 1 is for *strongly disagree* and 7 is for *strongly agree.* Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. The treated group is defined as respondents who live in lockdown states (i.e., in which the number of lockdown days is more than 7): ACT, VIC, NSW, QLD, and TAS. The control group is defined as respondents who live in lockdown-free states (i.e., in which lockdown days are equal to or less than 7): NT and SA, WA. The extensive margin estimation involves the full sample and utilizes the interaction between the treated group and the "After" dummy variable to capture treatment effects. In contrast, the intensive margin estimation focuses solely on the treated group and employs lockdown days as the continuous treatment variable. Both estimations control for marital status, labor market status, education level, and region-by-year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A2.5 Concurrent and cumulative effects simultaneously

Previous literature has suggested that loneliness can be viewed both as a stock variable, capturing cumulative events (e.g., Rokach and Brock, 1997; Vanhalst et al., 2013), and as a flow variable, encapsulating transitory feelings (e.g., Arpin and Mohr, 2019; Tian et al., 2017). To further explore these concepts, we utilize cumulative lockdown days and in lockdown *simultaneously* as an alternative specification to the baseline estimation (loneliness as a stock variable) and Table 7 Panel B (loneliness as a flow variable). The results are presented below in Table A6, and both the cumulative measure and the concurrent measure remain statistically insignificant across specifications. Consequently, our findings do not provide evidence that physical isolation is the determining factor of loneliness, either as a stock variable, or as a flow variable.

Table A6
Concurrent and cumulative lockdown.

VARIABLES	(1) Loneliness	(2) Loneliness	(3) Loneliness
Lockdown days	0.0409	0.0367	0.128
	(0.0269)	(0.0269)	(0.111)
Inlockdown = 1	−0.0387	−0.0331	−0.0578
	(0.0289)	(0.0288)	(0.145)
Observations	42,191	42,173	42,173
R-squared	0.000	0.004	0.006
Number of id	15,560	15,554	15,554
Ind FE	Yes	Yes	Yes
Ind controls	No	Yes	Yes
Region by year FE	No	No	Yes

Note: HILDA waves 2018–2019. Sample is limited to those who have repeated loneliness measures. Loneliness measure is 1 to 7 on *How much do you agree or disagree: I often feel very lonely,* where 1 is for *strongly disagree* and 7 is for *strongly agree.* Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in 2020, up until their interview dates, scaled by multiplying by 0.01. In lockdown=1 if an individual is in lockdown at the time of interview, 0 otherwise. The treated group is defined as respondents who live in lockdown states (i.e., in which the number of lockdown days is more than 7): ACT, VIC, NSW, QLD, and TAS. The control group is defined as respondents who live in lockdown-free states (i.e., in which lockdown days are equal to or less than 7): NT and SA, WA. Individual controls include marital status, labor market status, and education level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A2.6 Long-term effects

Our primary focus is to assess the immediate impact of physical isolation on loneliness, which led us to analyze data from the period of 2018–2020. We opted for this timeframe due to the low number of COVID cases uniquely in Australia during this period, which helps minimize the influence of COVID infections on loneliness. To complement this study design, we investigated the long-term effects of lockdowns on loneliness by incorporating data from the 2021 and 2022 waves. In this context, respondents experienced a maximum treatment effect of 262 days cumulatively. Fig. A1 illustrates the intensity of treatment by region. Regression results, as presented in Table A7, indicate that the lockdown point estimate sits at 0.013 with the inclusion of the 2021 wave, which is statistically insignificant, and at 0.006 with the addition of both the 2021 and 2022 waves, also statistically insignificant. These findings suggest that, within the scope of our study, the long-term effects of lockdowns on loneliness do not appear to be significant, aligning closely with our baseline findings.

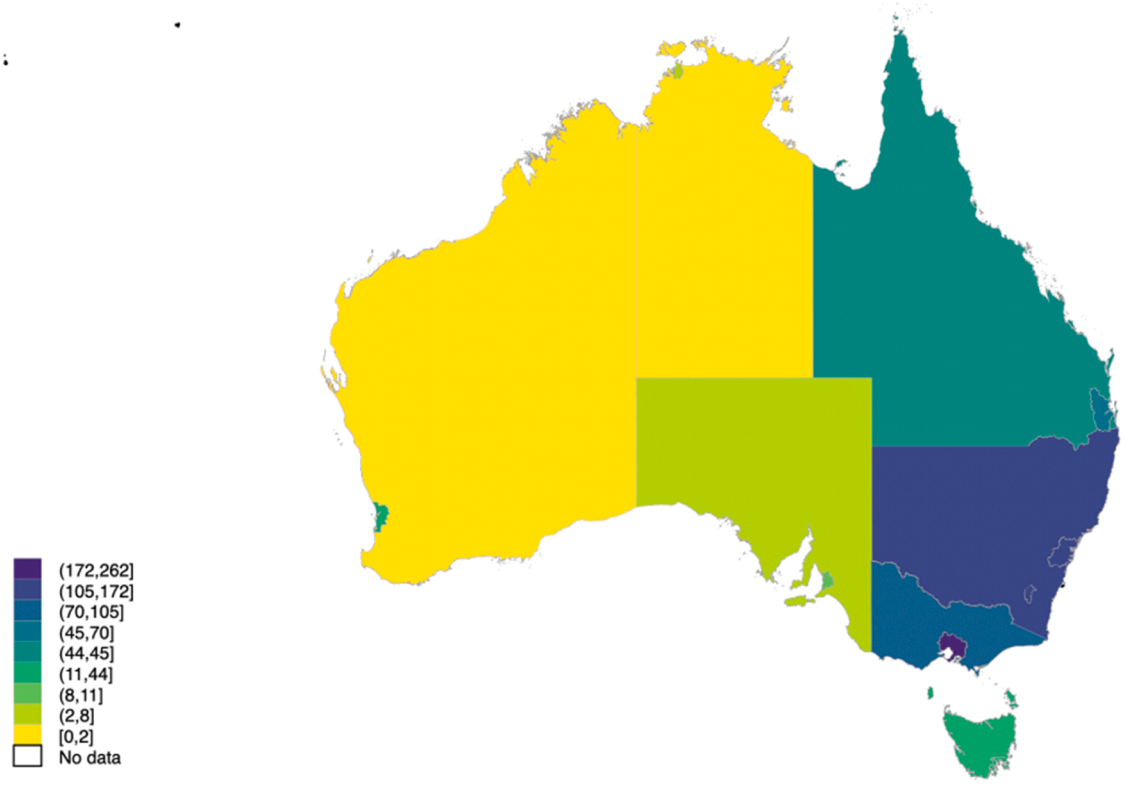

Fig. A1. Maximum lockdown days experienced by HILDA respondents by region 2020–2021.
Source: Maximum lockdown days are obtained by merging lockdown days at the Greater Capital City Statistical Area (GCCSA) and HILDA respondents' interview dates in 2020. Interview dates range in 2020 is 3-Aug-2020 to 21-Feb-2021, and in 2021 is 27 July 2021 to 14 March 2022. Treatment definition: the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in both 2020 and 2021, up until the interview date of the respective wave.

Table A7
Long term effects with the inclusion of waves 2021 and 2022.

VARIABLES	(1) Sample of 2018–2021	(2) Sample of 2018–2022
Lockdown days	0.0131	0.00618
	(0.0518)	(0.0471)
Observations	57,223	71,811
R-squared	0.007	0.008
Number of id	17,516	18,298

Note: HILDA waves 2018–2021 and waves 2018–2022. Sample is limited to those who have repeated loneliness measures. Loneliness measure is 1 to 7 on *How much do you agree or disagree: I often feel very lonely,* where 1 is for *strongly disagree* and 7 is for *strongly agree.* Lockdown days are defined as the cumulative number of days individuals experienced lockdown periods lasting more than 7 days in both 2020 and 2021, up until the interview date of the respective wave, scaled by multiplying by 0.01. The treated group is defined as respondents who live in lockdown states (i.e., in which the number of lockdown days is more than 7): ACT, VIC, NSW, QLD, and TAS. The control group is defined as respondents who live in lockdown-free states (i.e., in which lockdown days are equal to or less than 7): NT and SA, WA. Both estimations control for marital status, labor market status, education level, and region-by-year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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