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What buffered the impact of the COVID-19 pandemic on depression? A longitudinal study of caregivers of school aged children in Ireland

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The COVID-19 pandemic has wrought acute harm to global mental health, especially among vulnerable populations. We explore what factors in people's lives buffered the impact of the pandemic on depression; in particular, the role of social resources, economic resources, religiosity, and quality of their local environment. Drawing on three waves of longitudinal cohort data (two pre-pandemic waves and one pandemic-period wave) from primary caregivers of school-aged children in Ireland, we demonstrate that symptoms of depression increased sharply during the pandemic. However, depression symptomatology increased less steeply among caregivers who, pre-pandemic, had greater economic resources and lived in higher quality environments, but especially among those with greater social resources and those who exhibited greater religiosity. Path analysis suggests that different sources of buffering might mitigate harm via different pathways. While most buffering factors appear to cushion mental well-being by reducing stresses from increased care work, improving familial relations, and helping caregivers manage the closure of/return to schools, other drivers appear to cushion mental well-being by reducing health anxieties around COVID-19, increasing opportunities for outdoor exercise, and protecting household incomes. This study highlights how crisis-preparedness should invest in social infrastructure alongside medical infrastructure to protect societies from future pandemics.

Introduction

The COVID-19 pandemic has wrought acute harm to mental well-being across the globe. Such harm emerged from a constellation of negative-stressors, not least the impact on morbidity/mortality, but also health anxieties, lockdowns, the economic fallout, closure of key services, as well as the disruption of social networks (Borkowska and Laurence 2020; Chandola et al., 2022; Kim and Laurence, 2020; Nitschke et al., 2020). However, while the pandemic's onset was global, its impacts have not been shared equally across societies, with greater harm among groups such as the socio-economically disadvantaged or ethnic minorities (Pierce et al., 2020). One group facing a particular set of struggles has been caregivers of school-aged children, who experienced significantly worse mental well-being outcomes over the pandemic (Patrick et al., 2020; Pierce et al., 2020; Creswell et al., 2021; Xue and McMunn, 2021). This stemmed, in part, from the protracted closure of schools and childcare facilities, leading to a rapid and prolonged increase in care work demands, managing home schooling and work, coupled with a disconnection from support networks (Etheridge and Spantig, 2020; Xue and McMunn, 2021). However, while we know much about how the pandemic impacted mental well-being, we know less about what factors helped cushion the pandemic's effects on mental well-being; especially among vulnerable groups hardest hit (Laurence and Kim, 2021).

This paper examines how the pandemic impacted depression symptomology among a key vulnerable population—caregivers of school-aged children—and explores what social, economic, and local environmental factors helped mitigate any harm. Drawing on research into what factors buffer mental well-being against stressful life events, we test whether caregivers in possession of greater sources of protection before the pandemic (including social resources, economic

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resources, religiosity, and higher quality local environments) saw smaller increases in depression over the pandemic, and if so, through what pathways such buffering operated to reduce the pandemic's harm (Davydov et al., 2010; Ben-Zur and Michael, 2020). To do so, we mobilize Growing Up in Ireland (henceforth: GUI), a cohort study following a nationally representative sample of children born 2007–2008 and their caregivers. Drawing on three waves of data on primary caregivers (two pre-pandemic waves and one wave conducted during the pandemic), this paper advances our understanding of what factors cushion mental well-being during crises and the pathways through which such protection occurs.

Theoretical framework

Mental well-being, crises, and buffering factors

'Buffering' (or 'protective') factors are those elements in people's lives which cushion individuals from the harm that adverse life events, such as bereavement or job loss, can have on their mental well-being (Cohen and Wills, 1985; Ben-Zur and Michael, 2020). By association, the absence of such factors may exacerbate risks of harm from adversity (Cohen and Wills, 1985). Research into protective factors overlaps with the concept of 'resilience' in mental well-being research, which captures individuals' capacity to cope with/adapt positively to adverse life events, reducing their harm (Patel and Goodman, 2007; Davydov et al., 2010). Here, resilience is often seen as a personal trait and component of a positive psychological outlook (Zautra, Hall and Murray, 2008; Davydov et al., 2010; Ben-Zur and Michael, 2020). 'Buffering factors' do capture those elements of people's lives that may cushion well-being via inculcating psychological resilience; for example, where social support may enhance resilience to stressors through augmenting beliefs one is able to cope with stressful events (Davydov et al., 2010). However, 'buffering factors' may also cushion mental health through other mechanisms; for example, greater economic resources may buffer the harm of job loss given those with more economic resources may be better able to absorb its pecuniary impact, i.e., the buffering is not necessarily occurring through engendering psychological resilience. 'Buffering factors', therefore, form a broader concept, covering the factors in people's lives offering protection through multiple pathways.

Interest in factors which buffer mental well-being from adversity has led to examinations of their role in cushioning the impact of major crises/disasters, demonstrating how buffering factors can lessen the harms of significant financial crises like the Great Recession (Glonti et al., 2015), natural disasters such as Hurricane Katrina (Lê et al., 2013; Aldrich and Meyer, 2014), and health crises such as the Ebola outbreak (Cénat et al., 2020). Such cushioning-effects operate by reducing exposure to the stressors of a crisis (e.g. Glonti et al., 2015) or by reducing the harm that a given crisis-stressor might cause (e.g. Beggs, Haines and Hurlbert, 1996). Buffering factors are particularly important for vulnerable populations during crises who are both more likely to experience crisis-stressors and less able to absorb the stressors they do experience (Aldrich and Meyer, 2014).

This work raises a key question: to what extent did buffering factors also cushion mental well-being during the COVID-19 pandemic? Potentially, those buffering factors observed to cushion harm in previous crises may have operated similarly during the COVID-19 pandemic, given it involved similar stressor-pathways, such as health anxieties, financial stresses, and the trauma of losing friends/family (Chandola et al., 2022; Nitschke et al., 2020). However, the COVID-19 pandemic also exhibited important qualitative differences to previously studied crises, which could shape how, and which, buffers operated. For example, the pandemic involved potentially new stressor-pathways, such as where social/mobility restrictions and complete lockdowns generated stress through a prolonged disconnection from social networks (Borkowska and Laurence, 2020; Chandola et al., 2022). The pandemic also generated stresses from the closure of schools and services, especially among parents, generating strains from additional childcare responsibilities such as home schooling, alongside harming children's mental well-being (Patrick et al., 2020; Pierce, et al., 2020; Creswell et al., 2021). Whether buffering factors from prior crises cushioned these stressor-pathways remains to be seen. More importantly, however, the nature of this pandemic could have affected the ability of previously studied buffering factors to function in a similar fashion; for example, the social disconnection from lockdowns/social-distancing may have limited the ability of social resources to mitigate crisis-stressors in the same way as previous crises.

This paper therefore investigates what buffering factors cushioned the pandemic's harm to mental well-being, and how they operated compared to other crises (Gan and Best, 2021; Johnston, Kung and Shields, 2021; Laurence and Kim, 2021; Li et al., 2021). While studies document the role of psychological sources of resilience during the pandemic, such as self-efficacy (Johnston, Kung and Shields, 2021), fewer look at the broader buffering roles of more social and structural sources of protection. In the proceeding section, we outline four key social/structural buffering factors and their potential role during the pandemic.

Social capital and social resources

Social capital and social resources are well-documented sources of protection for mental well-being. Social capital comprises 'social networks and norms of reciprocity and trust' within which social resources are embedded, emerging from social connections including kinship/friendship ties, informal connections (e.g. neighbours), and formal ties from civic/social engagement (Putnam, 2000). Social capital primarily builds protection through social support, which can abate numerous stressors, including providing financial support, emotional support, and everyday help (Beggs, Haines and Hurlbert, 1996; Aldrich and Meyer, 2014; Lim and Laurence, 2015). This protective role also extends to large-scale crises, such as natural disasters/recessions, with community networks playing a particularly strong role (Beggs, Haines, and Hurlbert, 1996; Davydov et al., 2010; Frankenberg, Nobles and Sumantri, 2012; Lê et al., 2013; Ursano et al., 2014; Lim and Laurence, 2015). Accordingly, social capital could have cushioned mental well-being during the pandemic (Borkowska and Laurence, 2020; Chandola et al., 2022). However, given mobility restrictions significantly curtailed access to in-person social support, social resources could have played a weaker role. Alternatively, social resources embedded within households/localities may have become more important, and more dispersed ties less so, given an inability to access the latter. Cross-sectional studies find individuals reporting higher social capital during the pandemic evinced better mental well-being (Nitschke et al., 2020; Gan and Best, 2021; Laurence and Kim, 2021; Li et al., 2021), although longitudinal analyses *over* the pandemic yield more mixed evidence (Gan and Best, 2021; Johnston, Kung and Shields, 2021).

Economic resources

Economic resources (e.g. higher incomes/savings) are posited to buffer against adverse *economic* experiences in particular, helping individuals withstand sudden economic shocks (e.g. job loss), reducing their harm (Hobfoll, 2001; Davydov et al., 2010; Ben-Zur and Michael, 2020). Economic resources are thus particularly important for cushioning mental well-being during economic crises such as recessions (Glonti et al., 2015). However, studies of crises such as natural disasters find less evidence of a protective effect from non-pecuniary stressor-pathways (Frankenberg, Nobles and Sumantri, 2012; Ursano et al., 2014). Accordingly, economic resources may have cushioned pathways of financial stress during the pandemic but be less effective at cushioning non-pecuniary pathways such as health anxieties or care work (Chandola et al., 2022). Research into the COVID-19 pandemic indeed reveals a mixed cushioning role of economic resources (Johnston, Kung and Shields, 2021).

Religiosity

Religiosity is posited to buffer against adversity via fostering a stronger sense of meaning in life, optimism, and positive emotional regulation, which are known builders of psychological resilience, while also providing tools for meaning–making when adversity is experienced (Schwalm et al., 2022). Religious individuals are also often embedded within denser social networks, both within, and outside of, their religious communities, providing vital social support (Schwalm et al., 2022). Both religious beliefs and practices (e.g. attendance) have been posited to buffer stressful events (Dezutter, Soenens and Hutsebaut, 2006). Indeed, cross-sectional studies of pandemics have shown religiosity lessens their harm on mental well-being, although longitudinal analyses again yield weaker support (Cénat et al., 2020; Johnston, Kung and Shields, 2021).

Local areas and neighbourhood quality

One buffering factor potentially salient for the current pandemic is the quality of local environments. Green spaces can reduce stress and fatigue, and buffer economic disadvantage or family adversity, via improving mood through immersion in 'green views', encouraging physical activity, and providing opportunities for social interactions (Zautra, Hall and Murray, 2008; Flouri, Midouhas and Joshi, 2014; Wortzel et al., 2021). Traffic, noise, and pollution can also harm mental well-being and undermine individuals' ability to cope with stress (Reichert et al., 2020). Concurrently, local anti-social behaviour/disorder can foster feelings of powerlessness, undermining capacities to cope under stressful situations (Zautra, Hall and Murray, 2008).

During the current pandemic, with people largely constrained to local areas, neighbourhood quality may have become a particularly important buffering factor, given access to positive environmental influences was limited to local areas and given it increased duration of exposure to negative local environmental factors. Current research demonstrates that residents of disadvantaged areas saw larger declines in social capital (Borkowska and Laurence, 2020) and larger increases in mental distress (Bonomi Bezzo, Silva and van Ham, 2021), while suggestive evidence shows proximity to green spaces during the pandemic may have protected mental well-being (Wortzel et al., 2021).

Data and methods

Data and context

This study utilizes the 2008 Cohort of GUI, a cohort study following a nationally representative sample of all children born 2007–2008 in Ireland, alongside their primary and secondary caregivers. We draw on three waves of data on the child's primary caregivers, the majority of whom are mothers (98 per cent): wave 3 at which children were 5 years old (2013/2014), wave 5 (9 years old—2017/2018), and a survey conducted during the COVID-19 pandemic (12 years old—December 2020). The GUI has maintained high response rates, with 72 per cent of the original sample present in wave 5. The COVID-19 wave was an online survey, with a response rate of 45 per cent (n = 3901), with attrition higher among less advantaged backgrounds (e.g. lower income, lower parental education), single-parent households, and younger caregivers (ESRI, 2021). Survey weights are applied to correct for differential response. The sample is restricted to those primary caregivers who participated across all three waves (n = 3453). Listwise deletion of within-case missingness across key variables generates a balanced analytic sample of n = 8928 person-observations. We applied multiple imputation (MI) using chained equations to address within-case missingness; however, the results were substantively similar (we report unimputed findings).[1]

The GUI COVID-19 wave allows us to explore how the pandemic impacted mental well-being of primary caregivers in Ireland. From March to September 2020, Ireland experienced a nationwide lockdown, including schools/colleges/childcare facilities, alongside stay-at-home ordinances (except for supermarket visits, medical care, or exercise within a 2-kilometre radius of home) and bans on meeting with people from outside one's household. These restrictions created a unique set of care work demands among caregivers of school-aged children. This lockdown was followed by the reimposition of a 6-week lockdown in October 2020, alongside intermittent school closures and child/parent self-isolation thereafter. At the time of the COVID-19 GUI wave (4–31 December), there was a gradual re-opening of non-essential shops/services, followed by limited household visits from 18 December. This ended on 24 December when the country moved back into complete lockdown. The structure of the GUI data thus allows us to compare trends in respondent mental well-being before the pandemic (wave 3, 2014 to wave 5, 2018) with any changes that occurred 10 months after the pandemic began (wave 5, 2018 to COVID-19 wave, 2020).

Key measures

Depression

We study one aspect of respondents' mental well-being: their level of depression symptomology, using the Short-form Center for Epidemiological Studies Depression Scale, a shortened version of the Center for Epidemiologic Studies Depression Scale (CES-D) (Radloff, 1977; Turvey, Wallace and Herzog, 1999). Respondents were asked eight questions on how they felt during the past week on a 4-point Likert scale (0 = 'Rarely or none of the time (less than 1 day)', 1 = 'Some or a little of the time (1–2) days)', 2 = 'Occasionally or a moderate amount of the time (3–4 days)', and 3 = 'Most or all of the time (5–7 days)') (see Appendix Table A1 for full list of items).

The scale was designed to measure depression symptomology in general population settings, based on depressive symptoms observed in clinical cases, and focussing on the affective component of 'depressed mood' (Radloff, 1977). The scale has high internal validity and adequate test-retest repeatability and showed strong validity in discriminating clinical ratings of depression as well as strong relationships with significant negative life events and other depression measures (Radloff, 1977). Research has shown validity is maintained in the short-form scale (Carpenter et al., 1998). The measure contrasts somewhat with scales tapping broader components of 'psychological wellbeing', such as the General Health Questionnaire (GHQ), applied in previous studies of the COVID-19 pandemic. Although there is evidence both the CES-D and GHQ appear useful for detecting depression in general population surveys (e.g. Vilagut et al., 2016). Furthermore, research shows that CES-D depression symptomology scores also increased over the pandemic (van den Besselaar et al., 2021; Mooldijk et al., 2022).

The scale is designed so that scores to each of the eight questions are summed providing a total depression score ranging from 0 to 24. The measure is particularly suitable for our aims given it is measured at waves 3, 5, and the CV-19 wave to track respondents' depression symptomology both pre-pandemic and during the pandemic.

Buffering factors

Table 1 outlines the measures mobilized to capture the four sets of buffering factors, including social resources, religiosity, economic resources, and quality of local environments. All buffering factors are measured at wave 5, *prior to* the onset of the pandemic, apart from 'partner currently in the household' and whether a respondent was 'employed prior to the pandemic', which were retrospective questions available in the COVID-19 wave. In measurement at least, the variables can be equally interpreted as capturing the presence of risk factors (via the absence of buffering factors) which may exacerbate the impact of the pandemic; for example, the absence of social resources, absence of economic resources, living in a poor-quality environment (not living in higher quality environments), and lower religiosity.

Table 1 Measures of pre-pandemic buffering factors

Buffering factor set	Buffering factor type	Variable question	Variable scale	Measurement
Social resources	Scale of Local social capital	'People around here are willing to help their neighbours', 'You feel a strong sense of identity with your neighbourhood', 'Most people in your neighbourhood can be trusted'	1 = 'Strongly disagree' to 4 = 'Strongly Agree'	Mean scale: 1 = low social capital to 4 = high social capital*
		'How do you feel about your neighbourhood as a place for bringing up children?'	1 = 'Very poor' to 4 = 'Excellent'	
	Local family ties	'Do you have any family living in this area?'	0 = No, 1 = Yes	—
	Civic/social engagement	'Are you involved in any local voluntary organisations such as school groups, church groups, community or ethnic associations?'	0 = No, 1 = Yes	—
	Household ties	Are you currently living with your spouse or partner'	0 = No, 1 = Yes	—
	Perceived social support	'Overall, how do you feel about the amount of support or help you get from family or friends living outside your household?'	1 = 'I get enough help', 2 = 'Don't get enough help', 3 = 'Don't get any help at all', 4 = 'Don't need any help'	—
Religiosity	Religious service attendance	'How regularly do you attend religious service?'	0 = does not belong to a religion/never' to 5 = 'Daily'	—
	Religious affiliation	'Do you belong to a religious denomination…and if so, which one?'	0 = Do not belong to a religion, 1 = Roman Catholic, 2 = Other Christian, 3 = Other	—
	Religious identity	'In general, would you describe yourself as a religious person?'	1 = Not at all' to 5 = 'Extremely'	—
	Spiritual identity	'In general, would you describe yourself as a spiritual person?'	1 = Not at all' to 5 = 'Extremely'	—
Economic Resources	Welfare dependence	'Proportion of household income coming from social welfare (including Children's Allowance/ Child Benefit) payments?'	1 = 'None', 2 = 'Less than 5%', 3 = '5% to less than 20%', 4 = '20% to less than 50%, 5 = '50% to less than 75%', 6 = '75% to less than 100%', and 7 = '100%'	—
	Employment status	'Were you in employment just prior to the pandemic'	0 = No, 1 = Yes	—
	Perceived financial situation	'Concerning your household's total monthly or weekly income, with which degree of ease or difficulty is the household able to make ends meet? Would you say…'	1 = 'With great difficulty'; 2 = 'With difficulty'; 3 = 'With some difficulty'; 4 = 'Fairly easily'; 5 = 'Easily'; 6 = 'Very easily'	0 = 'Fairly easily' to 'very easily', and 1 = 'With some difficulty' to 'With great difficulty'
Quality of local area	Urban/rural dwelling	'Would you describe the place where the household is situated as being…?'	1 = 'Villages and open country', 2 = 'small towns', 3 = 'large towns', and 4 = 'Dublin city/other major cities'	—

Table 1. Continued

Buffering factor set	Buffering factor type	Variable question	Variable scale	Measurement
	Neighbourhood disorder	How common would you say that each of the things listed below is in your area? Rubbish and litter lying about How common would you say that each of the things listed below is in your area? Homes and gardens in bad condition	1 = 'Not at all common' to 4 = 'Very common'	Mean scale: 1 = low neighbourhood disorder to 4 = high neighbourhood disorder*
	Neighbourhood anti-social behaviour	How common would you say that each of the things listed below is in your area? Vandalism and deliberate damage to property How common would you say that each of the things listed below is in your area? People being drunk or taking drugs in public	1 = 'Not at all common' to 4 = 'Very common'	Mean scale: 1 = low neighbourhood anti-social behaviour to 4 = high neighbourhood anti-social behaviour*
	Heavy traffic	'There is heavy traffic on my street or road'	1 = 'Strongly Disagree' to 4 = 'Strongly Agree'	
	Accessibility to key services in the area	Could you tell me whether these services are available in or within relatively easy access of YOUR LOCAL AREA? A. Regular public transport, B. Social Welfare Office, C. GP or health clinic, D. Banking/Credit Union, E. Schools (primary or secondary). F. Garda station, G. Library. H. Essential grocery shopping, I. Post Office. J. Recreational facilities appropriate to a 9-yr old	0 = No, 1 = Yes	Count measure: how many services are available in a respondent's local area (0–10)
	Green spaces	'There are safe parks, playgrounds and play spaces in this area'	1 = 'Strongly Disagree' to 4 = 'Strongly Agree'	

Notes: *Factor analysis demonstrates these variables load highly (>0.4) on to a single high Eigen value (>1) factor, with an Alpha score > 0.7.

Pandemic stressor pathways

To understand the stressor-pathways through which buffering factors may cushion the pandemic's impact on mental well-being, we draw on questions asked within the COVID-19 survey-wave on experiences that respondents reported since the onset of the pandemic. The first set of stressors taps the impact of school closures, home working, and attendant childcare pressures (pathway name: 'care work stresses'), by generating a single mean score across four pandemic-period experiences (measured on a 3-point scale of 'Not true', 'Sometimes True', and 'Always True'): 'I had less time to myself', 'the increase in childcare responsibilities was stressful', 'supervising my child's schoolwork was stressful', and 'I spent more time than usual taking care of the children'.[2] The second pathway we tap is pandemic impacts on straining family relations (pathway name: 'worse familial/personal time') via a single mean score across three pandemic-period experiences: 'I enjoyed the time with my family', 'my family did more activities together', and 'I had a chance to slow down' (reverse coded from 'Always True', 'Sometimes true', to 'Not true'). Lastly, we use a single indicator of stresses related to transitions back into schooling reported by caregivers (pathway name: 'stressful school return'), with the question: 'I found my 12/13-year-old's return to school stressful' (no/yes).

We apply two measures tapping economic stressor-pathways: '[s]ince the start of the COVID-19 pandemic, did your household income…Increase a lot' to 'Fall a lot', on a 5-point scale (pathway name: 'reduced household income'); and whether a respondent reported a 'loss of employment (losing your job or temporary lay-off)' (No/Yes) during the pandemic (pathway name: 'job loss'). To measure health stressor-pathways, we tap respondents' own experience of having COVID-19: 'I have or had COVID-19' (no/yes) (pathway name: 'had/have COVID-19'). We also capture health anxieties about infection: 'I worried about the virus infecting someone in my family' ('Not true', 'Sometimes True' and 'Always True') (pathway name: 'family infection anxiety'). To examine physical activity/exercise pathways, we use a measure of time spent outdoors, where respondents were asked whether the pandemic had led them to spend 'more time outdoors' (reverse coded to 0 = yes, 1 = no) (pathway name: 'lack of outdoor activity'). An alternative measure on 'changes in physical activity' yielded similar results.

Controls

We include wave 5 (pre-pandemic) control variables, including: age, highest educational qualification, labour force status, years lived in neighbourhood, housing tenancy, social class, ethnicity, and an indicator of overcrowding (ratio of number of people in the household to number of bedrooms).

Methods and analytical approach

The analysis is divided into two stages. The first stage tests how the pandemic impacted depression among primary caregivers and whether any impact differed across buffering factors. It draws on all three waves of data (3, 5, and CV-19 wave). Multi-level mixed models are applied to account for the clustering of observations (level-1) within individuals (level-2). Dummy variables for survey-wave (wave 5 dummy excluded as baseline) test whether any trend in depression symptomology over the pandemic (wave 5 to COVID-19 wave) differs from trends before the pandemic (wave 3 to wave 5). To test whether buffering factors cushioned mental well-being, we add the indicators of pre-pandemic (wave 5) buffering factors to the model. These indicators are fixed at their wave 5 value across all three waves, allowing us to look at whether trends in depression both before and during the pandemic differed by pre-pandemic (wave 5) buffering factors. Interaction-terms between survey-wave dummies and indicators of pre-pandemic buffering will test whether any difference in trends across buffering resources are significant. Interaction-terms between survey-wave dummies and control variables will address possible confounding.

The second stage aims to explain any observed buffering-effects via path analysis. In particular, we test whether any cushioning-association between buffering factors and changes in depression over the pandemic could emerge from their role in shaping the type of pandemic-period stressors that caregivers experienced (e.g. childcare stress, health anxiety); that is, we look at whether our buffering factors might cushion mental well-being via an indirect effect[3] on reducing individuals' experiences of different stressors during the pandemic. To test the significance of multiple stressor-pathways we perform path analysis using generalized structural equation modelling (GSEM). This will focus on only 2 waves of data (wave 5 and the COVID-19 wave). The outcome will be a first-difference score capturing *changes* in depression with the onset of the pandemic (COVID-19 survey depression minus wave 5 depression). Predictors will be buffering indicators measured at wave 5. Potential pathways will be pandemic-period experiences measured during the COVID-19 wave. We therefore test how pre-pandemic buffering factors (wave 5) predict changes in depression (wave 5 to COVID-19 wave), and how far any relationship can be accounted for by the pandemic-period stressors that respondents experience (COVID-19 wave). Importantly, given our pandemic-period depression score and stressor-pathways are both measured in the COVID-19 wave, the analysis cannot make strong claims that stressors necessarily affect depression, given depression could feasibly shape experiences of stress. The GSEM approach allows us to estimate models simultaneously and combine estimation-results to perform formal significance testing of the indirect effects. The bootstrap method estimates the indirect effects with bias-corrected confidence intervals, based on 1,000 bootstrap samples (Preacher and Hayes, 2008).

Results

Depression symptomology and buffering factors over the pandemic

We first test how primary caregiver depression symptomology changed over the pandemic and explore whether buffering factors moderated any increases in depression. Full model results are in Appendix Table A2. Where a given buffering factor significantly moderates the pandemic-period trend in depression, we generate predicted scores to visualize changes in depression symptomology (non-significant characteristics are not graphed). Figure 1 (based on Model 1, Appendix Table A2) plots predicted depression scores over time absent of any covariates. Pre-pandemic, average depression scores among caregivers remained stable. However, by December 2020, depression scores sharply increased, nearly doubling.[4]

We next add pre-pandemic (wave 5) controls to our model, including interactions with period dummies, to test for trend heterogeneity across buffering characteristics (Model 2, Appendix Table A2). Trends did not differ by caregiver pre-pandemic age, education, tenure, social class, labour force status, ethnicity, or years lived in the community. However, depression trends were shaped by pre-pandemic household overcrowding. As Figure 2 shows (based on Model 2, Appendix Table A2), depression scores increased more sharply in more overcrowded households.[5]

We next examine the role of buffering factors. We first add all social resource measures into our model

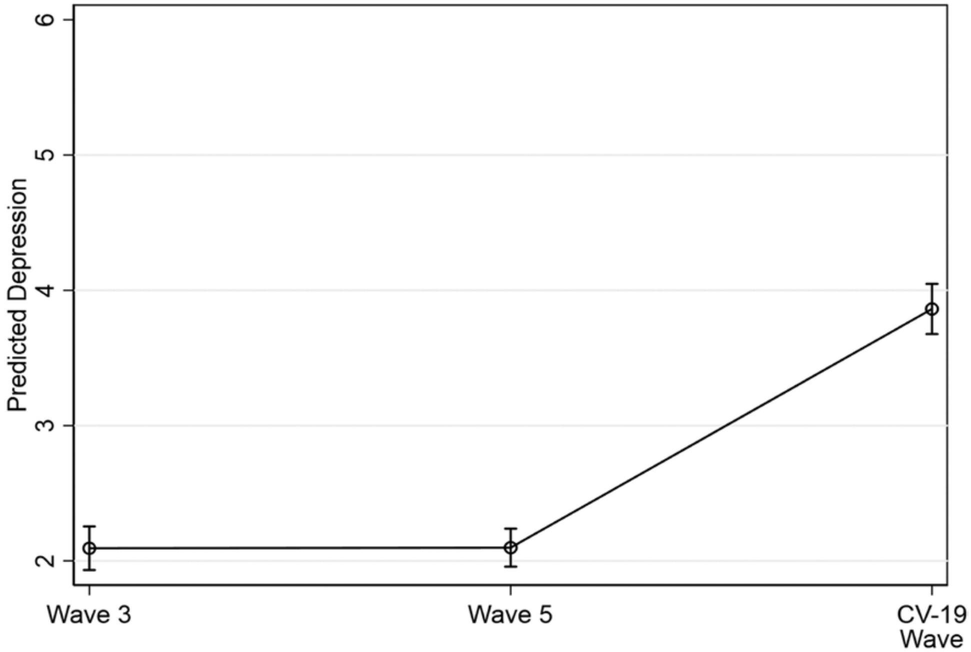

Figure 1 Trends in depression symptomology over the pandemic.

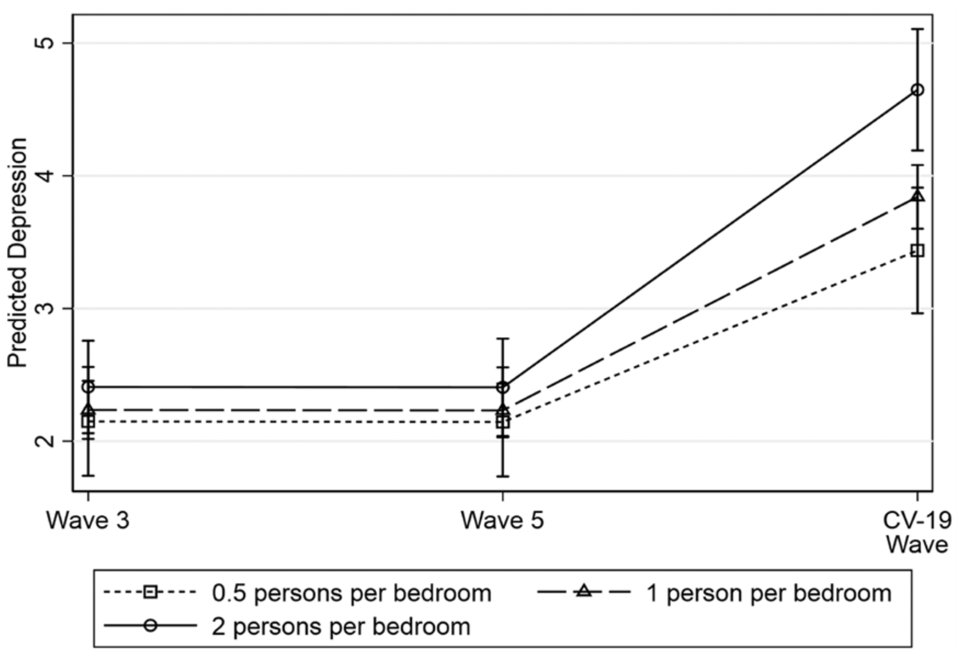

Figure 2 Trends in depression by level of pre-pandemic household overcrowding.

(with attendant period interaction-terms) (Model 3, Appendix Table A2). Pre-pandemic local volunteering or having family living in the local area did not significantly buffer depression during the pandemic (this latter measure did significantly cushion depression when entered alone but is rendered non-significant after including perceived family/friend social support). Several indicators of social resources, however, do independently moderate the trend in depression symptomology. Figure 3 (based on Model 3, Appendix Table A2) shows predicted depression scores among caregivers with/without a partner in the household. Before the pandemic, depression scores were around 1-point higher among single-caregiver households, and over the pandemic, depression increased at a lower rate among caregivers with a partner in the household, increasing over 1-point more for those without a partner.

Turning to pre-pandemic local social capital, Figure 4 (based on Model 3, Appendix Table A2) shows predicted depression scores among caregivers reporting high (maximum) and low (minimum) scores on the local social capital scale. Before the pandemic, higher local social capital was associated with lower depression scores. Over the pandemic, depression scores also increased less steeply in higher social capital areas, increasing by more than twice as much in low social capital areas. The additional increase in depression symptomology among those living in low compared to high social capital areas is twice the size of the increase in depression scores that occurs when someone moves from feeling they are able to financially make ends meet 'easily' to 'with difficulty'.[6]

Perceived social support from family/friends also moderates trends in depression symptomology. Figure 5 (based on Model 3, Appendix Table A2) shows predicted depression scores across waves by pre-pandemic help that caregivers received from family/friends. Model 3 tested whether trends in depression among caregivers responding they 'don't get any help', 'don't get enough help', or 'don't need any help' differed significantly from those responding they 'get enough help' (excluded baseline response). Generally, those reporting they 'do not get any help' or 'do not get enough help' report higher depression (at least by wave 5). However, over the pandemic, those who reported they 'do not get enough help' saw their depression score rise more steeply than those reporting they 'get enough help'.[7] This additional increase in depression symptomology among those who 'do not get enough help' is equivalent to someone seeing their self-reported health declining from being 'excellent' to only 'good'.

We next substitute social resources variables for economic resource measures in our model (with attendant period interaction-terms) (Model 4, Appendix Table A2). Economic resources play a weaker role, where trends in depression did not differ significantly among those who, pre-pandemic, were not employed, nor those who received a higher proportion of their income from welfare. Alternative measures returned identical findings (including household income and experience of rent/mortgage arrears). Where economic resources do matter is whether caregivers report they are able to financially make ends meet 'with difficulty' or 'easily'. In Figure 6 (based on Model 4, Appendix Table A2), those who were more easily able to make ends meet saw their depression score increase at a lower rate over the pandemic (significant at the $P < 0.1$ level).

We next substitute economic resources for local environment quality measures in our model (with attendant

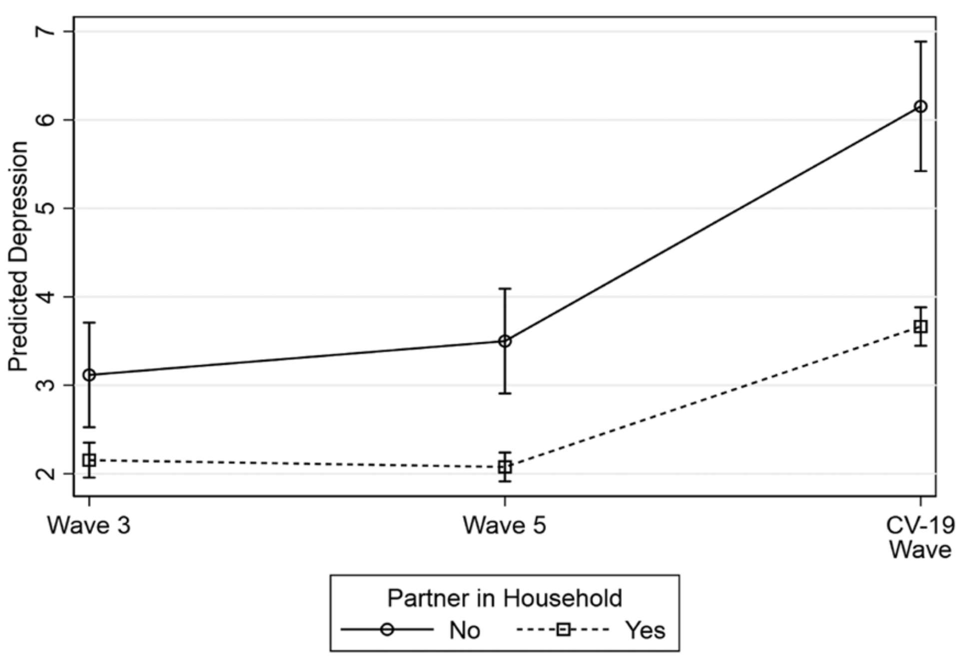

Figure 3 Trends in depression by pre-pandemic presence of partner in the household.

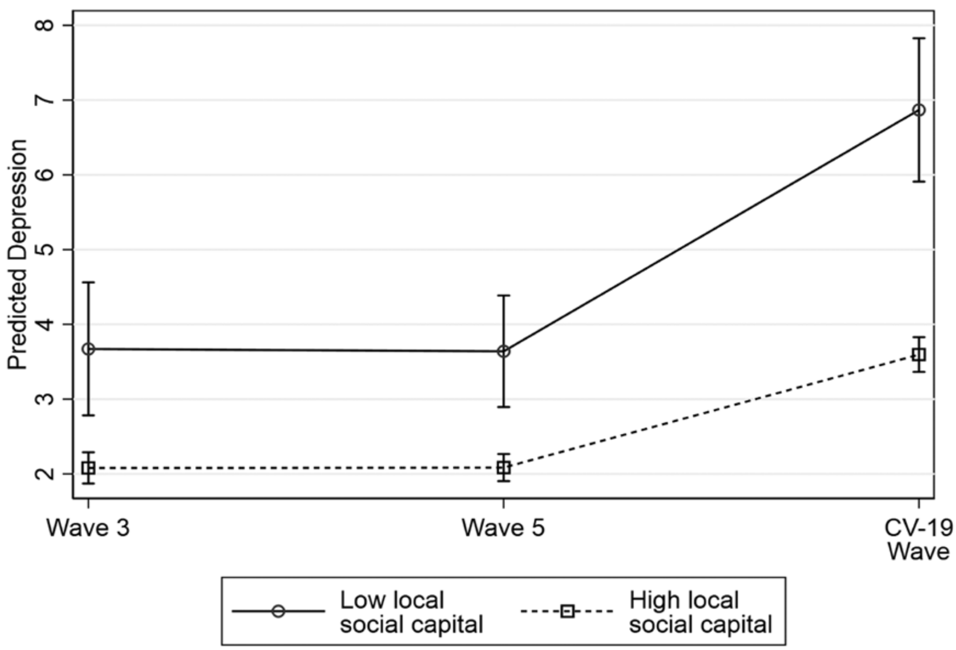

Figure 4 Trends in depression by level of pre-pandemic local social capital.

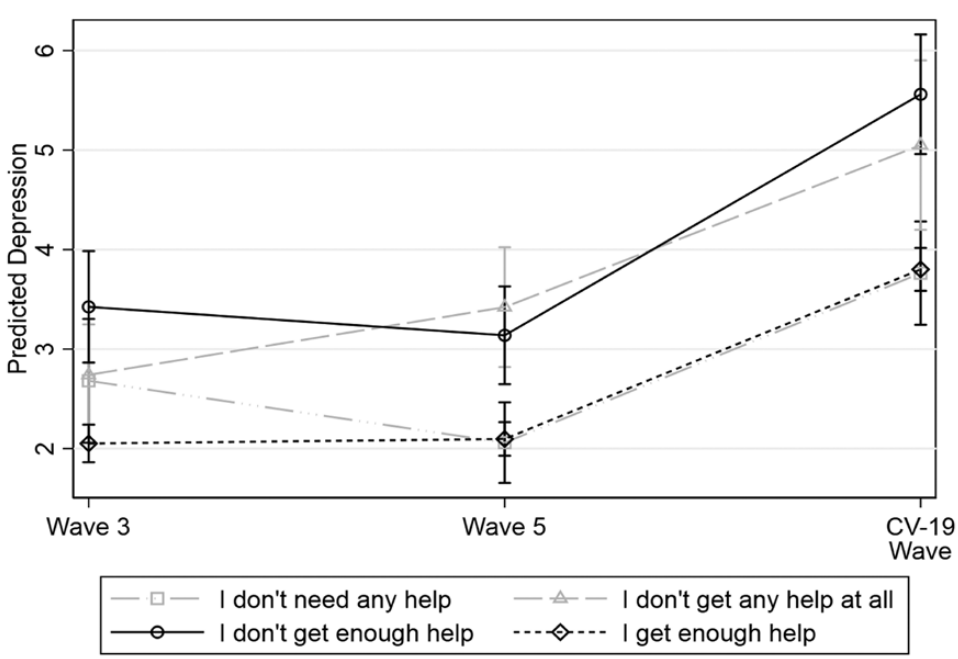

Figure 5 Trends in depression by level of pre-pandemic perceived friends/family social support. *Notes:* greyed trend lines show categories not significantly different from the baseline category 'I get enough help'.

period interaction-terms) (Model 5, Appendix Table A2). Neither number of essential services within the locality nor parks/play spaces for children appeared to exert a pandemic-buffering role. Depression did increase more during the pandemic among caregivers reporting more neighbourhood disorder/anti-social behaviour when these indicators were tested independently. However, when tested alongside urban/

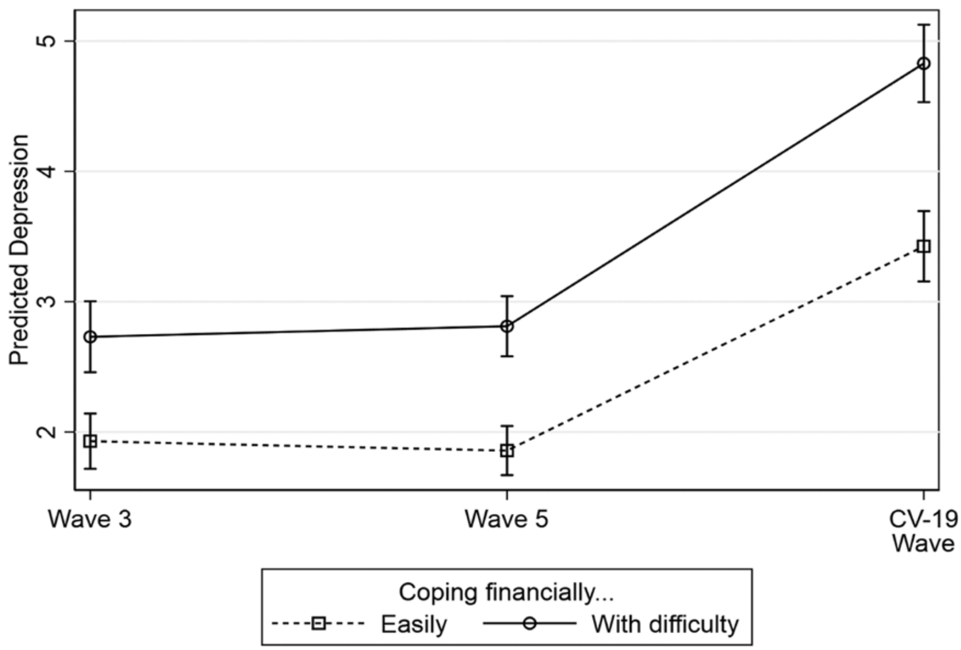

Figure 6 Trends in depression by level of pre-pandemic reports of how well caregiver is coping financially.

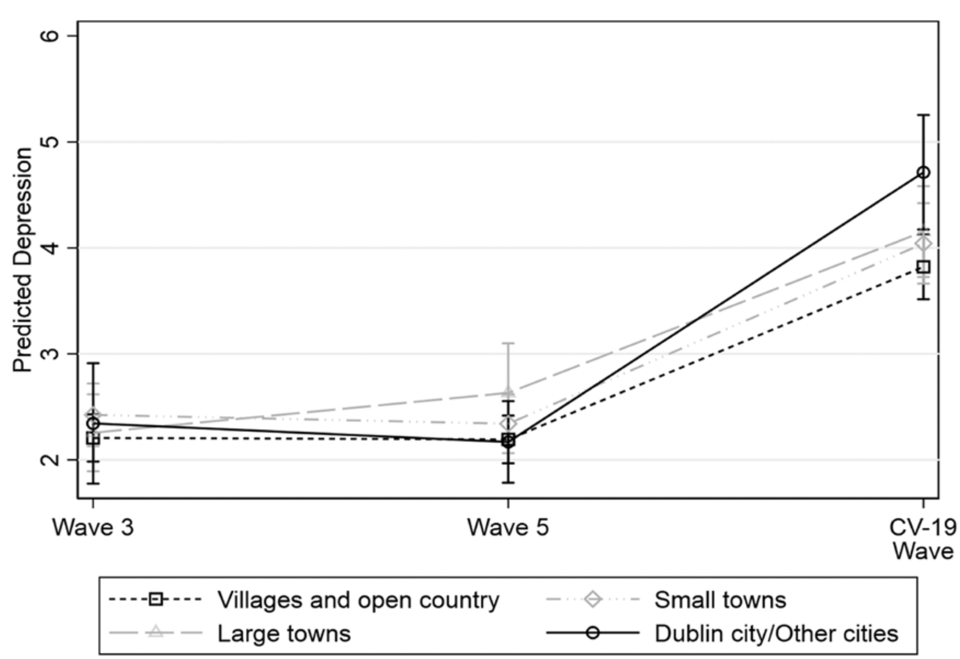

Figure 7 Trends in depression by pre-pandemic urbanity/rurality of caregiver residence. *Notes:* greyed trend lines show categories not significantly different from the baseline category 'resident in village/open country'.

rural residence, these associations became non-significant. Where local environment therefore does matter is whether caregivers live in urbanized (compared to rural) areas and the degree of traffic problems on caregivers' street/road. Figure 7 (based on Model 5, Appendix Table A2) plots predicted depression scores based on urban/rural environment. Model 5 tested whether depression trends differed significantly by whether respondents lived in 'small towns', 'large towns', or 'cities (including Dublin)', compared to 'villages/open country' (baseline category). During the pandemic, depression-scores rose at a significantly higher rate among residents of cities, compared to villages/open country (as well as residents of small and large towns). How far traffic in the local area is considered not to be a problem also exerted a cushioning effect. Figure 8 (based on Model 5, Appendix Table A2) shows that prior to the pandemic, there is little difference in depression between those strongly agreeing or strongly disagreeing heavy traffic is a problem. Over the pandemic, however, depression increased more among those strongly agreeing. The additional increases in depression symptomology in urban areas and among those strongly agreeing traffic is a problem is broadly equivalent to the increase in depression experienced when a partner leaves a household.

Lastly, we substitute local environment indicators for religiosity in our model (with attendant period interaction-terms) (Model 6, Appendix Table A2). Neither caregivers' denomination nor self-evaluation of their 'religiousness' or 'spirituality' shapes responses to the pandemic. However, frequency of pre-pandemic religious service attendance strongly moderates the pandemic-period trend in depression. Figure 9 (based on Model 6, Appendix Table A2) plots predicted depression scores by whether caregivers never attended church or attended it weekly/daily before the pandemic. Pre-pandemic, there is some evidence weekly/daily attenders report lower depression scores. However, during the pandemic, depression scores rose 2.5 times less amongst weekly/daily attenders compared to those who never attended. As with local social capital, the additional increase in depression symptomology experienced by those who never attended church (compared to weekly/daily attenders) is twice the size of the increase in depression symptomology occurring when someone moves from feeling they are able to financially make ends meet 'easily' to 'with difficulty'.

The preceding analysis (Models 1–6, Appendix Table A2) tested each set of buffering factors separately. In Model 7 (Appendix Table A2), we include all buffering factors to examine their relative importance when modelled together. Two observed factors become non-significant: overcrowding and whether caregivers are coping financially. However, despite a reduction in effect size, all other factors remain significant at the $P < 0.05$ level (although significance is reduced to $P < 0.1$ for perceived social support, living in cities, and heavy traffic). These findings suggest that social resources, local environment, and religiosity appear to play important, independent roles in cushioning caregiver depression over the pandemic.[8]

Pathways through which buffering operates

The second analytic stage examines evidence of the pathways through which buffering factors may cushion mental well-being. GSEM formally tests the

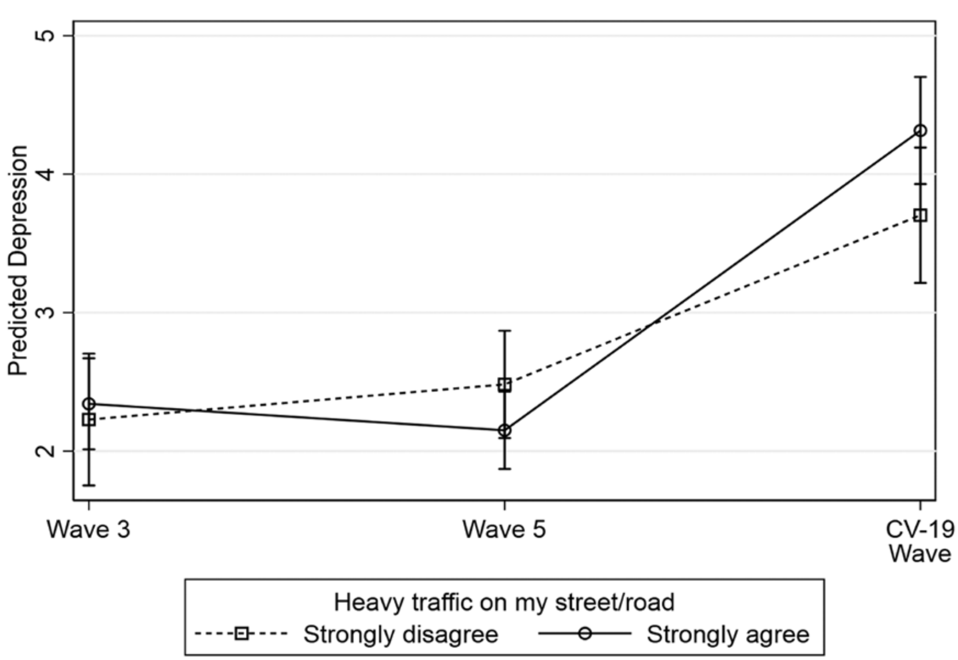

Figure 8 Trends in depression by pre-pandemic degree of traffic problems in neighbourhood.

indirect pathways between buffering factors (captured at wave 5) and changes in depression symptomology (between wave 5 and the COVID-19 wave) via experiences of each type of pandemic stressor (captured at the COVID-19 wave). Each set of buffering factors is again modelled separately (along with full controls). We report the direct effect (the association between a buffering factor and the change in depression symptomology after controlling for stressor-pathways) and indirect effects (the association between a buffering factor and a stressor-pathway, and a stressor-pathway and the change in depression symptomology) for each statistically significant buffering factor previously observed, along with the proportion of the total association that each indirect/direct pathway accounts for.

Table 2 examines the pandemic-risks to mental well-being from overcrowding, demonstrating a key reason why overcrowding is associated with larger rises in depression may be that caregivers struggled more with managing childcare/home schooling (30 per cent of total effect) and experienced worse family relations (18 per cent), with a

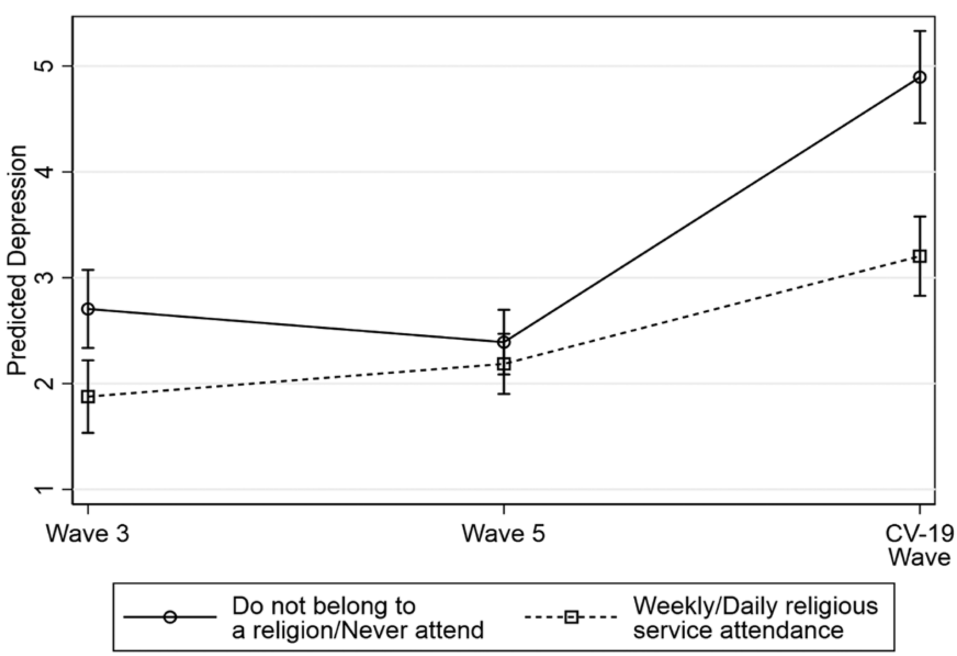

Figure 9 Trends in depression by pre-pandemic levels of religious service attendance.

Table 2 Stressor-pathways accounting for the role of household overcrowding

Buffering/risk factor	Indirect pathway	Coefficient	95 per cent confidence interval	% of total effect
Overcrowding	**Care work stresses**	**0.149**	**[0.087, 0.251]**	**30.48**
	Worse familial/personal time	**0.087**	**[0.033, 0.164]**	**17.9**
	Job loss	−0.008	[−0.06, 0.004]	−1.6
	Stressful school return	−0.024	[−0.086, 0.025]	−4.86
	Reduced household income	0.016	[−0.013, 0.065]	3.21
	Had/have COVID-19	0.005	[−0.014, 0.056]	0.98
	Family infection anxiety	**0.034**	**[0.002, 0.095]**	**6.96**
	Lack of outdoor activity	0.015	[−0.004, 0.061]	3.15
	Total indirect effect	**0.275**	**[0.115, 0.445]**	**56.22**
	Direct effect	0.214	[−0.249, 0.75]	43.78
	Total effect	**0.488**	**[0.007, 1.061]**	

Notes: indirect effects significant at the $P < 0.05$ level emboldened; bias-corrected 95 per cent confidence intervals.

non-trivial portion of the overall cushioning effect (7 per cent) accounted for by greater anxiety around infection of family members. Overall, over 50 per cent of the greater rise in depression scores in overcrowded households can be accounted for by the tested pathways.

Table 3 examines social resources. The cushioning role of local social capital appears to be accounted for primarily through its negative indirect association with home/family stressor-pathways, reducing stresses associated with childcare/home schooling (10 per cent) and the return of children to school (7 per cent), alongside better familial relations (9 per cent). Greater perceived social support also appears to cushion depression via home/family pathways, with those reporting they 'don't get enough help' from family/friends experiencing greater rises in depression scores (positive indirect effects on depression) due to struggles with childcare/home schooling (33 per cent) and stresses from their child returning to school (16 per cent). They also appear to experience greater depression scores due to higher anxieties about family infection. Having a partner in the household, however, has somewhat mixed relationships. As with other social resources buffering factors, it appears to reduce depression scores through its association with lower childcare/home schooling stress (11 per cent) and lower stresses associated with the return of children to school (9 per cent), alongside better familial relations (9 per cent) and more time spent outdoors (4 per cent). Interestingly, it also appears to protect caregivers through pecuniary pathways, with caregivers being less likely to experience a drop in household income (5 per cent). Yet, a partner in the household also appears to increase caregiver depression scores via anxieties of family infection (–4 per cent); 63 per cent of the buffering role of perceived social support is accounted for by these indirect effects. However, smaller portions of the cushioning effect are explained for local social capital (32 per cent) and partner in the household (22 per cent).

Turning to economic resources (Table 4), greater financial security appears to buffer mental well-being across a range of different stressor-pathways, including reducing stresses associated with childcare/home schooling (13 per cent) and the return of children to school (21 per cent), alongside better familial relations (10 per cent). However, it also appears to buffer against economic hardships (being associated with a reduced likelihood of experiencing a fall in household income (9 per cent)), reduced anxiety around family members becoming infected (9 per cent), and through caregivers spending more time outside (7 per cent). Two-thirds (67 per cent) of the overall cushioning effect of financial security is accounted for via these stressor-pathways.

Table 5 explores the pathways through which local environment may cushion mental well-being. Part of why caregivers in cities saw their depression rise more over the pandemic appears to be because city-residents struggled more in the home/family domain, including greater childcare/home schooling stresses (11 per cent) and the return of children to school (5 per cent), alongside less positive familial relations (11 per cent). However, another key potential pathway is through caregivers being less likely to spend time outdoors (9 per cent). A large proportion (40 per cent) of the overall buffering-effect of non-city living appears to be accounted for by these pathways. In comparison, only less time spent outdoors accounts for part of the effect of heavy traffic, and the vast majority (95 per cent) remains unexplained.

Turning to greater pre-pandemic religious service attendance (Table 6), little of the lower increase in depression scores among frequent pre-pandemic service attenders can be accounted for by the tested pathways, with no significant indirect effects. Indeed, 80 per cent of the total buffering-effect of religious attendance remains unexplained, suggesting the presence of other unmeasured pathways.

Discussion

This paper examined how the COVID-19 pandemic impacted depression symptomology among caregivers of school-aged children and what pre-pandemic characteristics buffered any harm. The results demonstrate that while, on average, depression symptomology rose steeply among caregivers during the pandemic, not all caregivers experienced an equal increase. Instead, multiple buffering factors appeared to protect their mental well-being.

Social resources play the most important buffering role (and their absence the strongest exacerbating role), in particular, local social capital. This might reflect the disconnection from wider social networks due to lockdowns, with only local ties able to offer any in-person support/interaction outside the household. Evidence suggests social resources primarily buffered the pandemic via reducing child/family stressors, with caregivers struggling less with care work, home schooling, and children's return to school, alongside experiencing better family relations, potentially providing the kinds of social support (practical/emotional) that help caregivers cope with the additional care work. However, some social resources also appear to provide a protective effect through reduced anxiety around family infection and against the economic shocks on income. Concurrently, social resources can also increase risks of depression over the pandemic, where a partner in the household generates greater anxieties around family infection, presumably given more people may increase fears of COVID-19 being brought into the household.

In line with current studies, economic resources appear less important for cushioning mental well-being during major crises (Johnston, Kung and Shields,

Table 3 Stressor-pathways accounting for the role of social resources

Buffering/risk factor	Indirect pathway	Coefficient	95 per cent confidence interval	% of total effect
Social capital index	**Care work stresses**	**−0.059**	**[−0.114, −0.021]**	**10.2**
	Worse familial/personal time	**−0.054**	**[−0.116, −0.017]**	**9.28**
	Job loss	0.004	[−0.002, 0.027]	−0.65
	Stressful school return	**−0.04**	**[−0.099, −0.01]**	**6.85**
	Reduced household income	0.003	[−0.015, 0.03]	−0.59
	Had/have COVID-19	−0.002	[−0.029, 0.012]	0.27
	Family infection anxiety	−0.016	[−0.051, 0.006]	2.83
	Lack of outdoor activity	**−0.022**	**[−0.062, −0.003]**	**3.87**
	Total indirect effect	**−0.185**	**[−0.304, −0.079]**	**32.07**
	Direct effect	**−0.392**	**[−0.725, −0.038]**	**67.93**
	Total effect	**−0.577**	**[−0.917, −0.219]**	
Don't get enough help (cf. Get enough)	**Care work stresses**	**0.203**	**[0.108, 0.326]**	**33.46**
	Worse familial/personal time	0.032	[−0.013, 0.103]	5.2
	Job loss	0.007	[−0.003, 0.059]	1.21
	Stressful school return	**0.098**	**[0.034, 0.22]**	**16.17**
	Reduced household income	0.007	[−0.03, 0.051]	1.12
	Had/have COVID-19	−0.002	[−0.044, 0.04]	−0.3
	Family infection anxiety	**0.043**	**[0.001, 0.105]**	**7.03**
	Lack of outdoor activity	−0.004	[−0.041, 0.024]	−0.58
	Total indirect effect	**0.384**	**[0.215, 0.576]**	**63.32**
	Direct effect	0.223	[−0.274, 0.857]	36.68
	Total effect	**0.607**	**[0.063, 1.216]**	
Partner in household	**Care work stresses**	**−0.113**	**[−0.228, −0.041]**	**10.84**
	Worse familial/personal time	**−0.093**	**[−0.205, −0.032]**	**8.98**
	Job loss	−0.016	[−0.084, 0.003]	1.54
	Stressful school return	**−0.094**	**[−0.214, −0.029]**	**9.07**
	Reduced household income	**−0.054**	**[−0.136, −0.015]**	**5.16**
	Had/have COVID-19	0.031	[−0.001, 0.144]	−3.01
	Family infection anxiety	**0.046**	**[0.001, 0.118]**	**−4.4**
	Lack of outdoor activity	**−0.045**	**[−0.113, −0.008]**	**4.37**
	Total indirect effect	**−0.231**	**[−0.46, −0.009]**	**22.23**
	Direct effect	**−0.808**	**[−1.562, −0.02]**	**77.77**
	Total effect	**−1.039**	**[−1.86, −0.295]**	

Notes: indirect effects significant at the $p<0.05$ level emboldened; bias-corrected 95 per cent confidence intervals.

2021). This could reflect national efforts to lessen the economic impacts of the pandemic, such as the Pandemic Unemployment Payment (PUP) in Ireland, providing relatively high levels of income replacement for those who lost their jobs. Where economic resources do matter, however, they appear to support mental well-being across a range of stressor-pathways, potentially allowing caregivers to better adapt to the pandemic; for example, reducing stresses of care work/home schooling (e.g. via tablets, laptops, high speed internet), better home/outdoor environments (e.g. larger gardens), or simply reducing stresses of financial anxiety (Xue and McMunn, 2021).

Contrary to expectations, few dimensions of local environment appear to offer a protective effect (nor exacerbate harm), despite lockdowns restricting mobility to people's local area. What appeared to matter was heavy traffic on one's street and whether caregivers were living in villages/cities, primarily buffering well-being via their link with more time spent outside.

Table 4 Stressor-pathways accounting for the role of economic resources

Buffering/risk factor	Indirect pathway	Coefficient	95 per cent confidence interval	% of total effect
Financial difficulty	**Care work stresses**	**0.061**	**[0.024, 0.117]**	**13.31**
	Worse familial/personal time	**0.047**	**[0.015, 0.099]**	**10.22**
	Job loss	0.005	[−0.004, 0.032]	1.02
	Stressful school return	**0.095**	**[0.042, 0.167]**	**20.57**
	Reduced household income	**0.041**	**[0.013, 0.086]**	**8.81**
	Had/have COVID-19	−0.015	[−0.076, 0.001]	−3.34
	Family infection anxiety	**0.042**	**[0.013, 0.088]**	**9.11**
	Lack of outdoor activity	**0.033**	**[0.008, 0.079]**	**7.08**
	Total indirect effect	**0.308**	**[0.191, 0.425]**	**66.78**
	Direct effect	0.153	[−0.209, 0.514]	33.22
	Total effect	**0.461**	**[0.069, 0.806]**	

Notes: indirect effects significant at the $P < 0.05$ level emboldened; bias-corrected 95 per cent confidence intervals.

Table 5 Stressor-pathways accounting for the role of local environment

Buffering/risk factor	Indirect pathway	Coefficient	95 per cent confidence interval	% of total effect
Local traffic	Care work stresses	0.003	[−0.015, 0.023]	0.98
	Worse familial/personal time	0.006	[−0.008, 0.027]	2.33
	Job loss	0.001	[−0.005, 0.011]	0.26
	Stressful school return	−0.005	[−0.027, 0.009]	−2.06
	Reduced household income	0.009	[−0.001, 0.029]	3.43
	Had/have COVID-19	0.004	[−0.002, 0.027]	1.66
	Family infection anxiety	0.006	[−0.006, 0.023]	2.28
	Lack of outdoor activity	**0.011**	**[0.002, 0.033]**	**4.35**
	Total indirect effect	0.012	[−0.039, 0.058]	4.53
	Direct effect	0.249	[0.069, 0.433]	95.47
	Total effect	**0.261**	**[0.079, 0.453]**	
Cities (cf. Villages)	**Care work stresses**	**0.103**	**[0.043, 0.195]**	**11.19**
	Worse familial/personal time	**0.097**	**[0.037, 0.185]**	**10.59**
	Job loss	−0.002	[−0.035, 0.011]	−0.26
	Stressful school return	**0.044**	**[0.004, 0.116]**	**4.75**
	Reduced household income	0.007	[−0.021, 0.054]	0.71
	Had/have COVID-19	0.012	[−0.014, 0.076]	1.3
	Family infection anxiety	0.026	[−0.009, 0.092]	2.83
	Lack of outdoor activity	**0.086**	**[0.029, 0.179]**	**9.33**
	Total indirect effect	**0.372**	**[0.225, 0.558]**	**40.45**
	Direct effect	0.547	[−0.069, 1.089]	59.55
	Total effect	**0.919**	**[0.303, 1.53]**	

Notes: indirect effects significant at the $P < 0.05$ level emboldened; bias-corrected 95 per cent confidence intervals.

Non-city living caregivers also experienced fewer care work/home life stressors, suggesting highly urbanized environments may have generated other forms of stress.

Frequent pre-pandemic religious service attendance also appeared to play a key cushioning role (and its absence an important risk factor). Despite prior work suggesting this might stem from access to social resources, attendance's cushioning role is not associated with the same stressor-pathways as social resources and remains strong even when modelled

Table 6 Stressor-pathways accounting for the role of religiosity

Buffering/risk factor	Indirect pathway	Coefficient	95 per cent confidence interval	% of total effect
Religious attendance	Time Pressures	−0.012	[−0.033, 0.004]	3.28
	Worse familial/personal time	−0.015	[−0.035, 0.001]	3.89
	Job loss	−0.004	[−0.021, 0.001]	1.15
	Stressful school return	−0.01	[−0.032, 0.001]	2.76
	Reduced household income	−0.002	[−0.014, 0.007]	0.42
	Had/have COVID-19	−0.009	[−0.041, 0.001]	2.48
	Family infection anxiety	0.001	[−0.013, 0.014]	-0.29
	Outdoor activity	−0.02	[−0.043, 0.001]	5.33
	Total indirect effect	−0.072	[−0.138, −0.025]	19.04
	Direct effect	−0.307	[−0.477, −0.158]	80.96
	Total effect	**−0.379**	**[−0.559, −0.219]**	

Notes: indirect effects significant at the $P < 0.05$ level emboldened; bias-corrected 95 per cent confidence interval.

alongside social resources. Religious attendance may instead be picking up religious beliefs, posited to generate psychological resilience. Indeed, recent work shows that religiosity acts as a protective against emotional distress via cognitive reappraisal (where negative conditions are reframed to shift perceptions of one's situation) and coping self-efficacy (people's confidence in their ability to manage stressful situations) (Dolcos et al., 2021).

Taken together, these findings make key contributions to understanding mental well-being during the COVID-19 pandemic and crisis-buffering more broadly. First, the use of longitudinal data suggests the findings on factors cushioning the pandemic are less likely to be solely driven by endogeneity. Second, the explicit testing of the associations between buffering factors, stressor-pathways, and mental well-being provides some of the first evidence into why buffering factors likely cushioned mental well-being. As might be expected, stressors associated with care work, home schooling and family life had the strongest associations with caregiver mental well-being, and buffering factors appear to have helped cushion harm via reducing these stressors. However, some buffering factors also appeared to reduce economic shocks, health anxieties, and enabled greater outdoor physical activity. In addition, different buffering factors appeared to cushion mental well-being through different pathways. For example, social resources are primarily associated with lower household stresses while local environment protective-effects are associated with greater outdoor activity. Third, the findings add to growing evidence that the pandemic widened pre-existing inequalities in mental well-being across societies. We identify several unexplored cleavages across which inequalities in mental well-being have widened (e.g. local social capital), whilst also showing that the pandemic opened up new inequalities in depression where there were none before (e.g. urban/rural residence). Lastly, the corollary of our findings is the insights they provide into factors which increase risk and exacerbate the harmful effects of crises on mental well-being. Individuals with fewer economic resources, living in lower quality environments, and especially those with fewer social resources and lower religiosity, are more at risk to the harm crises can exert on mental well-being.

Notwithstanding these insights, this study has limitations. The study only captures one dimension of mental well-being—depression symptomology—and the buffering-processes observed may operate differently for other dimensions (*although see* Laurence and Kim, 2021). Our measure of one's pre-pandemic buffering resources is captured 2 years prior to the onset of the pandemic. Potentially, caregivers' characteristics may have changed in the interceding years. In particular, the pandemic itself may have affected caregivers' levels of buffering factors (e.g. social resources), and thus our tests are specifically on whether higher pre-pandemic levels of buffering factors mattered. Similarly, our pandemic-period measurement was in December 2020. This could potentially underestimate the impact of the pandemic, given it is 10 months after the first lockdown began and shape which buffering factors appear most important; for example, local environment may have played a more important role at the height of the first lockdown. In addition, seasonality-effects on mental well-being could over-estimate the pandemic-effect, given the December survey-period. Part of the observed pandemic impact on caregiver depression could also be driven (as discussed) by changes stemming from their child entering adolescence, although testing demonstrated this might only account for a small portion of the observed increase.[4] Still, part of the cushioning-effects could be driven by enabling caregivers to better adapt to their child's transition to adolescence. Caution must also be taken in inferring causality between the stressor-pathways and depression, given the stressor-pathways and pandemic-period depression score were both measured in the same wave. The pandemic may have increased depression, making caregivers less able to cope with other aspects of their lives. Future research that can address time-ordering of stressor-experiences and mental well-being could provide stronger tests.

Lastly, the modelling approach and number of tests undertaken, while increasing robustness in some respects, may increase risks of false positives. Applying the Benjamini and Hochberg (1995) correction, most findings remain robust at a false discovery rate (FDR) of 10 per cent (apart from perceived social support, overcrowding, 'coping financially', and 'local traffic problems'). This count, however, is significantly reduced at an FDR of 5 per cent. Future research replicating the findings will be critical to further validate the results.

In sum, this study adds to evidence that cultivating buffering characteristics, especially social resources, can strengthen societies' capacity to weather crises. Integrating such perspectives into crisis management could help protect societies, particularly among groups disproportionately affected by a crisis, and potentially weaken the well-documented long-term scarring that adverse life events have over people's lives.

Notes

1. Fifteen imputed-datasets were created with estimates combined according to Rubin's rules (*available on request*).
2. Factor analysis demonstrates these four variables load highly (>0.4) on to a single high Eigen value (>1) factor, with an Alpha score >0.7.
3. We use the term indirect effect as applied in mediation analysis to refer to the relationship between the buffering factor, stressor-pathway and depression, although we test associations between variables.
4. This pandemic increase in PCG depression may be partly driven by changes occurring with their child entering adolescence, given the known physical/emotional/relational changes during this transition. To explore this, we draw on a second GUI cohort dataset of children born in 1998 and examine how PCG depression symptomology changes during a similar period (when their child ages from 9 to 13). Over this period, PCG depression rose by 0.3 points. Part of the PCG increase in depression during the pandemic could be driven by their child ageing. However, given depression-scores rose by 2 points, the pandemic is likely driving most of the rise.
5. This was not an artefact of a higher number of children in the household.
6. All effect size comparisons are calculated from two-wave fixed-effects models (GUI waves 3 and 5) testing the impact of either perceived financial situation, self-reported health, or a partner leaving one's household on PCG depression (results available on request).
7. The 'don't get enough help' group also saw their depression rise at a greater rate than those reporting they 'don't need any help' and 'don't get any help at all'.
8. We also explored whether the pandemic had heterogeneous impacts based on pre-pandemic levels of depression, or whether pre-pandemic depression levels could account for any patterns of buffering observed, both by running a model including a lagged measure of depression, and also running a model including interactions with period dummies. However, the main substantive findings remain unchanged.

Data Availability

The Growing Up in Ireland 2008 Cohort data can be accessed here: https://www.ucd.ie/issda/data/growingupinirelandgui/. This provides researchers access to an anonymised microdata file (AMF) version of the data. The present study uses a Researcher Microdata File (RMF) version of the data, which contains more detailed measures and additional variables. The RMF version of the data is accessed remotely via a Virtual Desktop Infrastructure by submitting an application to the Irish Central Statistics Office (CSO). Details on how to apply can be found here: https://www.cso.ie/en/aboutus/lgdp/csodatapolicies/dataforresearchers/rmfapplicationprocedure/.

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Appendix

Table A1 Items contained in the Short-form Center for Epidemiological Studies Depression Scale (CES-D)

Question
1. I felt I could not shake off the blues even with the help from my family or friends
2. I felt depressed
3. I thought my life had been a failure
4. I felt fearful
5. My sleep was restless
6. I felt lonely
7. I had crying spells
8. I felt sad

Table A2 Multi-level random-effects modelling of impact of the pandemic on depression and the role of buffering factors

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Variable group	Time only	Controls	Social resources	Economic resources	Local area quality	Religiosity	All buffers
Outcome	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**
Wave (cf. Wave 5)							
Wave 3	−0.004	−0.389	−1.306	−1.204	0.084	−0.917	−1.775
	(0.102)	(1.232)	(1.560)	(1.398)	(1.708)	(1.373)	(1.897)
CV-19 Wave	1.765***	1.063	3.556*	0.338	0.066	0.233	2.509
	(0.109)	(1.240)	(1.635)	(1.404)	(1.510)	(1.388)	(1.877)
Age		−0.021	−0.025	−0.022	−0.016	−0.016	−0.020
		(0.014)	(0.016)	(0.015)	(0.016)	(0.015)	(0.015)
Wave 3 * Age		0.012	0.018	0.017	0.013	0.011	0.019
		(0.020)	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)
CV-19 Wave * Age		−0.008	0.000	0.001	−0.007	0.002	−0.006
		(0.021)	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)
Overcrowding		0.174	0.186	−0.036	−0.002	0.136	0.011
		(0.246)	(0.260)	(0.259)	(0.263)	(0.257)	(0.265)
Wave 3 * Overcrowding		−0.001	−0.166	−0.125	−0.079	−0.076	−0.187
		(0.297)	(0.316)	(0.314)	(0.321)	(0.310)	(0.321)
CV-19 Wave * Overcrowding		0.634*	0.543	0.462	0.390	0.569+	0.428
		(0.323)	(0.339)	(0.343)	(0.331)	(0.331)	(0.341)
Qualifications (cf. Junior Cert or less)							
Leaving Cert		−0.736+	−0.834+	−0.988*	−0.979*	−0.952*	−0.844+
		(0.397)	(0.433)	(0.424)	(0.426)	(0.428)	(0.436)
Non-Degree		−0.496	−0.405	−0.588	−0.579	−0.503	−0.465
		(0.360)	(0.409)	(0.397)	(0.397)	(0.401)	(0.417)
Degree of more		−0.417	−0.505	−0.608	−0.612	−0.644	−0.591
		(0.358)	(0.407)	(0.393)	(0.393)	(0.394)	(0.416)
Wave 3 * Leaving Cert		0.550	0.897	0.985+	0.911	0.810	0.907
		(0.517)	(0.555)	(0.563)	(0.570)	(0.550)	(0.559)
Wave 3 * Non-Degree		0.002	0.152	0.238	0.169	0.019	0.239
		(0.481)	(0.515)	(0.530)	(0.527)	(0.515)	(0.518)
Wave 3 * Degree of more		−0.452	−0.185	−0.105	−0.170	−0.267	−0.036
		(0.494)	(0.527)	(0.538)	(0.542)	(0.525)	(0.533)
CV-19 Wave * Leaving Cert		0.265	0.820	0.770	0.833	0.712	0.833
		(0.624)	(0.646)	(0.657)	(0.635)	(0.650)	(0.637)
CV-19 Wave * Non-Degree		0.413	0.692	0.636	0.724	0.607	0.714
		(0.586)	(0.627)	(0.622)	(0.605)	(0.615)	(0.625)
CV-19 Wave * Degree of more		0.355	0.716	0.723	0.737	0.686	0.748
		(0.589)	(0.637)	(0.622)	(0.601)	(0.612)	(0.625)
N years in area		−0.006	0.002	−0.005	−0.007	−0.001	0.001
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Wave 3 * N years in area		0.005	0.000	0.003	0.004	0.003	−0.002
		(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
CV-19 Wave * N years in area		−0.010	−0.006	−0.009	−0.015	−0.008	−0.009
		(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)

Table A2. Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Variable group	Time only	Controls	Social resources	Economic resources	Local area quality	Religiosity	**All buffers**
Outcome	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**
Employee (incl. Apprenticeship or Community Employment)							
Self-employed		0.091	0.057	0.062	0.072	−0.065	−0.037
		(0.193)	(0.192)	(0.201)	(0.203)	(0.206)	(0.192)
Student full-time		1.424	1.466	1.412	1.491	1.429	1.559
		(0.965)	(0.981)	(0.967)	(0.980)	(1.000)	(0.998)
Unemployed, looking for a job		1.302*	0.632	0.800	0.712	0.847	0.551
		(0.600)	(0.707)	(0.735)	(0.748)	(0.722)	(0.763)
Long-term sick/disability		2.063**	1.894**	2.054**	1.965**	2.058**	1.709*
		(0.737)	(0.704)	(0.740)	(0.722)	(0.735)	(0.675)
Looking after home or family		0.553***	0.487**	0.486*	0.461**	0.449**	0.464*
		(0.166)	(0.176)	(0.201)	(0.177)	(0.173)	(0.201)
Other, Farmer, state training		−0.151	−0.293	−0.424	−0.343	−0.309	−0.303
		(0.543)	(0.567)	(0.569)	(0.568)	(0.575)	(0.543)
Wave 3 * Self-employed		0.050	0.025	0.044	0.014	0.101	0.035
		(0.262)	(0.268)	(0.284)	(0.280)	(0.285)	(0.273)
Wave 3 * Student full-time		0.651	0.666	0.637	0.720	0.653	0.467
		(0.817)	(0.864)	(0.828)	(0.840)	(0.853)	(0.909)
Wave 3 * Unemployed		−0.615	0.294	−0.409	0.284	0.282	−0.263
		(0.721)	(0.829)	(0.858)	(0.867)	(0.846)	(0.879)
Wave 3 * Long-term sick/ disability		0.826	0.729	0.397	0.713	0.625	0.656
		(0.952)	(0.916)	(0.952)	(0.888)	(0.910)	(0.851)
Wave 3 * Looking after home or family		−0.358	−0.289	−0.404	−0.234	−0.249	−0.357
		(0.228)	(0.246)	(0.293)	(0.244)	(0.244)	(0.289)
Wave 3 * Other, Farmer, state training		0.077	0.418	0.320	0.465	0.516	0.293
		(0.835)	(0.896)	(0.869)	(0.900)	(0.854)	(0.852)
CV-19 Wave * Self-employed		0.325	0.425	0.339	0.371	0.314	0.409
		(0.335)	(0.356)	(0.357)	(0.352)	(0.359)	(0.354)
CV-19 Wave * Student full-time		−1.138	−0.864	−1.072	−1.012	−1.126	−1.075
		(1.327)	(1.296)	(1.357)	(1.317)	(1.395)	(1.328)
CV-19 Wave * Unemployed		0.362	0.611	0.640	0.907	0.849	0.609
		(0.818)	(0.948)	(0.967)	(0.953)	(0.979)	(0.947)
CV-19 Wave * Long-term sick/disability		1.089	0.915	0.668	0.884	0.877	0.680
		(1.034)	(1.050)	(1.043)	(1.081)	(1.048)	(1.045)
CV-19 Wave * Looking after home or family		−0.257	−0.110	−0.343	−0.158	−0.191	−0.302
		(0.255)	(0.270)	(0.313)	(0.267)	(0.264)	(0.307)
CV-19 Wave * Other, Farmer, state training		−0.078	0.225	−0.083	0.064	0.197	0.123
		(0.784)	(0.895)	(0.841)	(0.839)	(0.814)	(0.865)
Tenancy (cf. Owner)							
Social housing		0.727*	0.302	0.732+	0.602	0.862*	0.265
		(0.360)	(0.378)	(0.386)	(0.390)	(0.388)	(0.376)
Private rent		0.818**	0.589*	0.679*	0.775**	0.837**	0.567*
		(0.266)	(0.284)	(0.286)	(0.290)	(0.290)	(0.277)

Table A2. Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Variable group	Time only	Controls	Social resources	Economic resources	Local area quality	Religiosity	**All buffers**
Outcome	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**
Other		0.407	0.116	0.556	0.607	0.552	0.364
		(0.723)	(0.683)	(0.721)	(0.695)	(0.739)	(0.666)
Wave 3 * Social housing		−0.607	−0.515	−0.774+	−0.525	−0.735	−0.698
		(0.436)	(0.449)	(0.455)	(0.466)	(0.458)	(0.440)
Wave 3 * Private rent		−0.569	−0.483	−0.540	−0.462	−0.529	−0.492
		(0.356)	(0.373)	(0.382)	(0.384)	(0.386)	(0.358)
Wave 3 * Other		1.291	0.437	0.249	0.190	0.193	0.257
		(0.804)	(0.506)	(0.534)	(0.522)	(0.502)	(0.520)
CV-19 Wave * Social housing		0.452	−0.006	0.375	0.161	0.266	−0.173
		(0.544)	(0.566)	(0.596)	(0.567)	(0.564)	(0.556)
CV-19 Wave * Private rent		−0.522	−0.616	−0.436	−0.593	−0.385	−0.796*
		(0.363)	(0.407)	(0.399)	(0.399)	(0.390)	(0.403)
CV-19 Wave * Other		−0.442	−0.988	−0.622	−0.909	−0.728	−1.131
		(0.998)	(1.155)	(1.148)	(1.171)	(1.086)	(1.099)
Social Class (cf. Professional/managerial and technical workers)							
Non-manual		−0.120	−0.173	−0.192	−0.193	−0.119	−0.222
		(0.171)	(0.172)	(0.179)	(0.179)	(0.178)	(0.171)
Skilled manual		−0.172	−0.299	−0.335	−0.235	−0.257	−0.307
		(0.226)	(0.241)	(0.247)	(0.250)	(0.248)	(0.240)
Semi-skilled/Unskilled		−0.164	−0.201	−0.273	−0.179	−0.128	−0.263
		(0.286)	(0.307)	(0.318)	(0.314)	(0.310)	(0.315)
All others gainfully occupied/unknown		0.947*	0.500	0.686	0.916*	0.823+	0.431
		(0.452)	(0.485)	(0.516)	(0.466)	(0.467)	(0.510)
Wave 3 * Non-manual		0.310	0.420	0.387	0.463+	0.441	0.453
		(0.268)	(0.280)	(0.285)	(0.280)	(0.282)	(0.279)
Wave 3 * Skilled manual		−0.212	0.012	−0.117	0.015	0.033	−0.156
		(0.314)	(0.339)	(0.349)	(0.336)	(0.347)	(0.334)
Wave 3 * Semi-skilled/ Unskilled		0.078	0.060	−0.027	0.032	0.031	−0.052
		(0.400)	(0.423)	(0.432)	(0.425)	(0.423)	(0.428)
Wave 3 * All others gainfully occupied/ unknown		−0.466	−0.387	−1.097+	−0.528	−0.458	−0.890
		(0.535)	(0.584)	(0.614)	(0.582)	(0.583)	(0.601)
CV-19 Wave * Non-manual		0.592*	0.605*	0.628*	0.651*	0.668*	0.653*
		(0.287)	(0.295)	(0.303)	(0.289)	(0.293)	(0.294)
CV-19 Wave * Skilled manual		0.168	0.379	0.353	0.487	0.442	0.399
		(0.352)	(0.373)	(0.376)	(0.382)	(0.374)	(0.375)
CV-19 Wave * Semi-skilled/Unskilled		0.600	0.492	0.492	0.539	0.609	0.548
		(0.427)	(0.435)	(0.456)	(0.451)	(0.454)	(0.430)
CV-19 Wave * All others gainfully occupied/ unknown		−0.313	−0.765	−0.479	−0.214	−0.379	−0.648
		(0.588)	(0.617)	(0.675)	(0.629)	(0.625)	(0.659)
Ethnicity (cf. White Irish)							
Other white		0.136	0.087	0.190	0.208	0.171	0.016
		(0.290)	(0.315)	(0.317)	(0.313)	(0.305)	(0.300)

Table A2. Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Variable group	Time only	Controls	Social resources	Economic resources	Local area quality	Religiosity	All buffers
Outcome	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**
Non-White		−0.730*	−0.841*	−0.592	−0.500	−0.411	−0.626
		(0.338)	(0.366)	(0.385)	(0.391)	(0.423)	(0.417)
Wave 3 * Other white		0.004	−0.022	−0.049	−0.040	0.005	0.152
		(0.357)	(0.390)	(0.390)	(0.386)	(0.379)	(0.372)
Wave 3 * Non-White		0.996+	1.082+	0.815	0.976	1.231+	1.480*
		(0.552)	(0.600)	(0.632)	(0.655)	(0.689)	(0.665)
CV-19 Wave * Other white		−0.259	−0.575	−0.491	−0.437	−0.526	−0.557
		(0.384)	(0.410)	(0.405)	(0.406)	(0.409)	(0.400)
CV-19 Wave * Non-White		−0.229	−0.796	−0.675	−0.640	−0.583	−0.606
		(0.490)	(0.533)	(0.539)	(0.528)	(0.582)	(0.592)
Social resources							
Partner in household (cf. No)							
Yes			−1.422***				−1.241***
			(0.329)				(0.323)
Wave 3 * Partner in HH			0.459				0.436
			(0.409)				(0.394)
CV-19 Wave * Partner in HH			−1.067*				−0.933*
			(0.470)				(0.470)
Local volunteer (cf. No)							
Yes			−0.076				−0.037
			(0.136)				(0.135)
Wave 3 * Local volunteer			0.019				0.022
			(0.190)				(0.190)
CV-19 Wave * Local volunteer			0.065				0.113
			(0.234)				(0.232)
Family in local area (cf. No)							
Yes			−0.079				−0.077
			(0.157)				(0.156)
Wave 3 * Family in local area			0.359				0.403+
			(0.227)				(0.228)
CV-19 Wave * Family in local area			−0.258				−0.174
			(0.246)				(0.243)
Local social capital			−0.519***				−0.297+
			(0.141)				(0.158)
Wave 3 * Local social capital			−0.012				−0.006
			(0.206)				(0.221)
CV-19 Wave * Local social capital			−0.572**				−0.485*
			(0.208)				(0.236)
Perceived social support (cf. I get enough help)							
Don't need any help			−0.037				−0.046
			(0.219)				(0.221)
Don't get any help at all			1.325***				1.226***
			(0.316)				(0.301)

Table A2. Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Variable group	Time only	Controls	Social resources	Economic resources	Local area quality	Religiosity	**All buffers**
Outcome	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**
Don't get enough help			1.042***				0.865***
			(0.260)				(0.257)
Wave 3 * Don't need any help			0.667+				0.668+
			(0.404)				(0.386)
Wave 3 * Don't get any help at all			−0.635+				−0.564
			(0.368)				(0.349)
Wave 3 * Don't get enough help			0.331				0.329
			(0.376)				(0.363)
CV-19 Wave * Don't need any help			−0.001				−0.097
			(0.313)				(0.305)
CV-19 Wave * Don't get any help at all			−0.076				−0.042
			(0.554)				(0.533)
CV-19 Wave * Don't get enough help			0.718*				0.629+
			(0.354)				(0.345)
Economic resources							
Coping financially (cf. Easily)							
With difficulty				0.954***			0.759***
				(0.147)			(0.146)
Wave 3 * With difficulty				−0.153			−0.134
				(0.204)			(0.201)
CV-19 Wave * With difficulty				0.450+			0.305
				(0.230)			(0.230)
Employment before pandemic (cf. Employed)							
Not employed				−0.059			−0.064
				(0.225)			(0.225)
Wave 3 * Not employed				0.194			0.213
				(0.328)			(0.316)
CV-19 * Not employed				0.277			0.385
				(0.332)			(0.322)
Proportion income via welfare				−0.022			−0.080
				(0.085)			(0.082)
Wave 3 * Proportion income via welfare				0.233*			0.230*
				(0.118)			(0.112)
CV-19 Wave * Proportion income via welfare				0.006			−0.069
				(0.130)			(0.129)
Local environment							
Urban/rural (cf. Villages, open country)							
Small towns					0.148		0.060
					(0.184)		(0.188)
Large towns					0.439		0.265
					(0.275)		(0.259)
Dublin city/Other cities					−0.024		−0.171
					(0.227)		(0.223)

Table A2. Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Variable group	Time only	Controls	Social resources	Economic resources	Local area quality	Religiosity	**All buffers**
Outcome	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**
Wave 3 * Small towns					0.069		0.040
					(0.237)		(0.241)
Wave 3 * Large towns					−0.390		−0.409
					(0.360)		(0.337)
Wave 3 * Dublin city/ Other cities					0.161		0.169
					(0.360)		(0.345)
CV-19 Wave * Small towns					0.073		−0.136
					(0.285)		(0.304)
CV-19 Wave * Large towns					−0.107		−0.342
					(0.350)		(0.353)
CV-19 Wave * Dublin city/Other cities					0.916*		0.646+
					(0.369)		(0.362)
Local deterioration					0.230+		0.138
					(0.137)		(0.133)
Wave 3 * Local deterioration					0.266		0.270
					(0.228)		(0.214)
CV-19 Wave * Local deterioration					0.035		−0.036
					(0.211)		(0.202)
Local anti-social behaviour					0.419*		0.260
					(0.173)		(0.169)
Wave 3 * Local anti-social behaviour					−0.406		−0.362
					(0.258)		(0.265)
CV-19 Wave * Local anti-social behaviour					0.231		0.088
					(0.264)		(0.263)
Local traffic					−0.083		−0.106
					(0.075)		(0.074)
Wave 3 * Local traffic					0.111		0.118
					(0.116)		(0.113)
CV-19 Wave * Local traffic					0.236*		0.224+
					(0.117)		(0.115)
N of local essential services					0.011		0.030
					(0.042)		(0.040)
Wave 3 * N of local essential services					−0.034		−0.049
					(0.056)		(0.054)
CV-19 Wave * N of local essential services					0.003		0.011
					(0.059)		(0.057)
Local park availability					−0.072		−0.024
					(0.093)		(0.095)
Wave 3 * Local park availability					−0.186		−0.159
					(0.140)		(0.143)
CV-19 Wave * Local park availability					−0.047		0.007
					(0.147)		(0.148)

Table A2. Continued

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Variable group	Time only	Controls	Social resources	Economic resources	Local area quality	Religiosity	**All buffers**
Outcome	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**	**Depress.**
Religiosity							
Denomination (cf. Do not belong to a religion)							
Roman Catholic						–0.415	–0.389
						(0.288)	(0.284)
Other Christian						–0.629+	–0.695+
						(0.376)	(0.369)
Non-Christian						–0.048	–0.311
						(0.523)	(0.532)
Wave 3 * Catholic						0.764+	0.807*
						(0.401)	(0.393)
Wave 3 * Other Christian						0.491	0.575
						(0.456)	(0.450)
Wave 3 * Non-Christian						–0.566	–0.320
						(0.813)	(0.846)
CV-19 Wave * Catholic						0.613	0.690
						(0.433)	(0.431)
CV-19 Wave * Other Christian						0.357	0.455
						(0.519)	(0.516)
CV-19 Wave * Non-Christian						0.712	0.409
						(0.806)	(0.790)
Religious attendance						–0.051	–0.006
						(0.065)	(0.065)
Wave 3 * Religious attendance						–0.156	–0.164+
						(0.101)	(0.097)
CV-19 Wave * Religious attendance						–0.372***	–0.342**
						(0.105)	(0.113)
Religious person						–0.346***	–0.287**
						(0.103)	(0.098)
Wave 3 * Religious person						0.252+	0.207
						(0.141)	(0.137)
CV-19 Wave * Religious person						0.243	0.274
						(0.170)	(0.168)
Spiritual person						0.199*	0.155+
						(0.090)	(0.084)
Wave 3 * Spiritual person						–0.066	–0.041
						(0.111)	(0.105)
CV-19 Wave * Spiritual person						0.100	0.079
						(0.133)	(0.126)
N (observations)	8988	8988	8988	8988	8988	8988	8988
N (individuals)	2996	2996	2996	2996	2996	2996	2996

Notes: Significance levels: + 0.1; *0.05; **0.01; ***0.001.