Societal movement restrictions and adverse mental health outcomes

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Abstract

During the COVID-19 pandemic, governments struggled to find the right balance between re-strictive measures to contain the spread of the virus, and the effects of these measures on people's psychological wellbeing. This paper investigates the relationship between limitations to mobility and mental health for the UK population during the COVID-19 pandemic, using a unique combination of high-frequency mobility data from Google and longitudinal monthly survey data collected during the pandemic. We find a strong and robust correlation between high-frequency mobility data and established low-frequency mental health survey data. We show that increased residential stationarity predicts a mental wellbeing deterioration even when we control for regional COVID-19 prevalence and lockdown stringency. We uncover heterogeneity in this relationship. Particularly high levels of distress are seen in young, healthy people living alone with an active working life. Women also suffer more from mobility restrictions than men, especially if they have young children.

Introduction

The eruption of the COVID-19 pandemic and the varied reactions of governments across the globe have generated important lessons about the extent to which our wellbeing depends on "mobility": namely, being able to function as human beings that interact with one another in a world where economic activities (e.g., production, consumption, and education) – and socialization with others in general – involve moving across physical space. While mobility was the key to opening up the potential benefits of globalisation, "lockdowns" – the prohibition against leaving one's residence unless carrying out a few essential services – were extensively used to contain the spread of COVID-19 (i.e., the disease caused by the novel coronavirus, SARS-CoV-2) in many parts of the world.

As a nonpharmaceutical intervention (NPI) to limit the morbidity and mortality associated with COVID-19, lockdowns have been effective in a number of settings, both in ex-ante modeling exercises (1) and in ex-post evaluations (2–4). However, their use as a generic response to "flatten the curve"0F0F has been "unprecedented in scale, scope, and duration" (5, p. 1375) and deemed a "cure […] worse than the disease" (6) for aggravating the mental health of those under restrictions1F1F. COVID-19 itself, of course, also causes mental distress. COVID-19-related deaths of family and friends are adverse shocks, and there is the prevailing fear of being infected (7), as well as financial insecurity brought about by the pandemic (8). The fact that lockdowns reduce the spread of COVID-19 and the transmission of SARS-CoV-2 can improve the mental wellbeing of the population. However, while lockdowns have reduced the burden associated with the disease itself, these government measures designed to restrict mobility, such as "stay-at-home" or "shelter-in-place" orders, are strongly associated with adverse impacts on wellbeing, especially on mental health (9–10). The mental pressures of a pandemic were described by Thucydides in his *History of the Peloponnesian War*: "The most terrible thing of all was the despair into which people fell when they realized that they had caught the plague; for they would immediately adopt an attitude of utter hopelessness, and, by giving in in this way, would lose their powers of resistance… For when people were afraid to visit the sick, then they died with no one to look after them" (11, p. 89)

A priori, it is not clear which impact on mental health – a positive one associated with reduced prevalence of COVID-19 or a negative one associated with physical isolation – is larger in magnitude, nor is it clear if the net effect 'switches' from benefiting to harming society when restrictions last beyond a certain point.

Part of the problem is that information on mental health is typically collected retrospectively through ad hoc surveys. Hence, one learns about the effect of current restrictions with a lag, which can vary from weeks – as is the case in the UK where information is collected monthly from a representative panel of households – to months or years, as most other countries include health-related questions only in annual surveys. This delay, in turn, sheds light on the problem only when it has already grown, with possibly tragic consequences from self-harm, suicides, and domestic violence, to name a few. Thus, from a policy perspective, it is worth understanding whether ubiquitous digital data can offer alternative methods of providing faster societal and policy feedback, particularly in times of crises. Smartphones, for example, generate instant tracking via a digital human footprint or digital bread crumbs of a society (12–14). Thus, it is a natural avenue through which we might understand whether such reality mining can increase policy validity beyond the common method of primary data collection via surveys.

The COVID-19 pandemic is a unique setting for exploring the empirical relationship between easily collectable, high-frequency data, such as mobility (or lack of mobility) constructed from information on the movement of people (e.g., via Google for those whose location history settings are enabled) and psychological and mental wellbeing. Thus, in this paper, we combine data on mobility sourced from Google's publicly available Community Mobility Reports with monthly data on mental health generated by high-quality longitudinal studies from the UK to measure the relationship between mobility and mental health. In doing so, we add to the growing literature that examines mental wellbeing during the pandemic (15–21). For the United Kingdom, previous work focused on investigating changes in mental health during the pandemic, such as (8, 22–37). Most of these studies use survey data to analyse changes in mental health during the COVID-19 pandemic and focus on the impact of observable characteristics of individuals in mitigating the effects on mental wellbeing. However, these studies collectively provide insight only on mental health behaviour specifically during the COVID-19 pandemic. This leaves a gap in understanding the relationship between mental health and mobility behaviour, a dynamic that can offer important lessons for policymakers in the use of insights from "big data" (characterized by high volume, high velocity, and wide variety).

The analysis in this paper uses mental health data from the UK Understanding Society longitudinal dataset. An important advantage of this monthly survey is that the Understanding Society study allows us to track a strongly validated measure of mental wellbeing: the short-form, 12-item General Health Questionnaire (GHQ-12) "Caseness score" (38). Previous studies (10, 39) have proxied for mental wellbeing using Google Trends data generated by searches performed on Google. Another stream of studies have used helpline calls to examine the impact of COVID-19 on mental health (40–43).

We model variations in GHQ Caseness score across various territories in the UK as a function of the percentage change in the time spent at home obtained through Google's Community Mobility Reports. The use of this variable improves on previous studies (e.g., 9) that have relied on an event-study approach using, as triggers, the date that lockdowns took effect. Moreover, we use individual, region, and wave fixed effects to disentangle the specific effects of restrictions in mobility on mental wellbeing. Our findings are applicable across a number of research areas within health, inclusive of vulnerable sub-populations such as the unemployed, physically disabled, and older, isolated age groups.

Our results come from regressing region-level GHQ Caseness scores against the percentage change in the time spent at home (residential stationarity), along with a set of socioeconomic and demographic control variables as well as geographic, time, and individual fixed effects. We show that more time spent at home predicts a worsening of mental wellbeing, even after accounting for the prevalence of COVID-19 in the region and the general stringency of the lockdown. In terms of the magnitude, a one-standard-deviation decrease in residential mobility is associated with an increase of 0.087 standard deviations in GHQ Caseness score (indicating worse mental health). There is some evidence of heterogeneity in the extent to which mental wellbeing can be predicted by the amount of time spent at home. In particular, it appears that older people, men, and those with partners exhibit weaker correlations, as well as those people living in rural areas, those who own their houses outright (i.e., not paying off a mortgage), those who were not working, and those who were less healthy.

Understanding the importance of high-frequency data by validating with survey data has received limited attention within a social science perspective. Social scientists have focused on macro-based and cultural indicators relative to mobility, including the understanding of labour, employment, and mobility across differing occupations (44), or have focused on behavioural aspects around mobility such as risk (45), trust (46) or personality characteristics (47). This leaves current social science research with a narrower focus for truly understanding the relationship between mobility and mental health, particularly within specific contexts such as the UK (36, 48–49), and despite the fact that research within health sciences has shown the importance of the relationship between mobility behaviours and mental health outcomes (50–52). Further, most of the existing studies do not include detailed information on participants' pre-pandemic traits and do not model the existence of common time-invariant characteristics across regions, individuals, and time.

[1] The curve being "flattened" is the epidemic curve, which represents the number of people infected over time.

[2] The so-called "Great Barrington Declaration" – signed by a number of prominent scientists and academics – has advocated for "focused protection" instead, where the most vulnerable to COVID-19 are "shielded" from the virus.

Results

Figure 1 displays a choropleth map of regional average mental health (GHQ Caseness) in the UK. London's residents experienced the worst subjective wellbeing for the entire duration of the dataset, including during the pre-pandemic period. Immediately after the declaration of the pandemic in March 2020, we observe a radical decline in people's mental wellbeing. April 2020 is clearly the worst month. Generally, mental wellbeing showed an improvement as summer approached, which brought with it an easing of lockdown restrictions; this was followed by a deterioration again in winter with lockdowns reinstated. These panels in Fig. 1 portend our main results from the more sophisticated analysis – that increased mobility restrictions due to the lockdowns likely resulted in poorer mental health.

We find a very strong correlation between movement reduction and average mental health outcomes (prevalence in mental health issues). Figure 2 presents the linear fit between the mobility measure and mental health outcomes aggregated by regions and survey waves (averages). The correlation coefficients of regional-level mobility change and mental health are 0.61 and 0.87 for the two derivative measures of mental health (GHQ in a Likert scale, which ranges from 0 to 36 (Fig. 2a), and GHQ Caseness score, which ranges from 0 to 12 (Fig. 2b); in both cases, higher values correspond to worse mental health), respectively.

The largest change in the duration spent at home is experienced in the earlier parts of the pandemic (April and May 2020, for instance, have the darker shades of green, which appear toward the right of each panel). This period is also associated with poorer mental health. A decrease in mobility at the societal level is also strongly associated with poorer mental health across all 12 regions. In Fig. 3, each dot represents the monthly average within each region, with the change in time spent at home (the horizontal axis) representing the deviation from the baseline at January 2020. Darker colours represent later waves.

Residents of London again display the strongest relationship ($\rho = 0.97$) between the lockdown restrictions and mental health. For instance, people living in London experienced the most radical change in the duration spent at home – about 30% at its most extreme (in April 2020), which is associated with the worst average GHQ Caseness score in Fig. 2. Visually, the other regions are fairly similar to each other, with correlation ranging from 0.77 (Northern Ireland) to 0.95 (West Midlands).

In Table 1, we show the main regression results using individual level observations with the GHQ Caseness score as the outcome variable. As a benchmark, we begin with a bivariate model (Column 1) and subsequently include COVID test results and socio-demographic variables (Column 2), pre-existing mental health or long-term illness history (Column 3), COVID-19 prevalence and government stringency level in the last seven days (Column 4), region fixed effects (Column 5), wave fixed effects (Column 6), and individual fixed effects (Column 7). The estimated relationship between movement reduction and mental health deterioration is statistically significant at least at the 5% level. The main results are also robust to all specifications including the alternative derivative measure of mental health (i.e., Likert; Supplementary Table 2), using the past-14 days average for mobility, COVID-19 cases, and stringency measures (Supplementary Table 3), and clustering standard errors at the region or region and survey wave levels (Supplementary Table 4).2F2F

Table 1
Movement restrictions worsen mental wellbeing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in duration of time spent at home (%)	0.046***	0.047***	0.047***	0.046***	0.047***	0.037**	0.040**
	(0.00131)	(0.00135)	(0.00136)	(0.00186)	(0.00188)	(0.0128)	(0.0126)
COVID-19 positive		0.21***	0.20***	0.13***	0.14***	0.13***	0.11**
		(0.0343)	(0.0337)	(0.0348)	(0.0349)	(0.0354)	(0.0384)
Age		-0.018***	-0.014***	-0.015***	-0.015***	-0.015***	
		(0.00202)	(0.00187)	(0.00187)	(0.00187)	(0.00187)	
Female		0.74***	0.56***	0.55***	0.56***	0.56***	
		(0.0406)	(0.0367)	(0.0367)	(0.0367)	(0.0367)	
Marital status							
Married/civil partnership		-0.31***	-0.19**	-0.18**	-0.18**	-0.18**	
		(0.0679)	(0.0622)	(0.0622)	(0.0621)	(0.0621)	
Separated/divorced/widowed		0.0074	-0.014	0.0017	-0.0029	-0.0047	
		(0.0847)	(0.0752)	(0.0752)	(0.0753)	(0.0753)	
Living with partner		-0.29***	-0.21***	-0.21***	-0.21***	-0.21***	-0.16**
		(0.0457)	(0.0440)	(0.0440)	(0.0440)	(0.0440)	(0.0558)
Education							
No qualification		-0.24*	-0.32**	-0.31**	-0.32**	-0.31**	
		(0.114)	(0.0979)	(0.0979)	(0.0979)	(0.0978)	
Other qualification		-0.11	-0.14†	-0.13†	-0.13	-0.13	
		(0.0924)	(0.0801)	(0.0801)	(0.0802)	(0.0802)	
A level		-0.016	0.0050	0.0023	-0.00077	-0.00088	
		(0.0667)	(0.0596)	(0.0596)	(0.0596)	(0.0596)	
Other higher degree		0.077	0.093	0.095	0.092	0.092	
		(0.0733)	(0.0652)	(0.0652)	(0.0652)	(0.0652)	
Degree		0.18**	0.19***	0.19***	0.20***	0.20***	
		(0.0596)	(0.0535)	(0.0535)	(0.0538)	(0.0538)	
Live in rural area		-0.070	-0.043	-0.044	-0.046	-0.047	
		(0.0451)	(0.0405)	(0.0406)	(0.0420)	(0.0420)	
Housing status							

Notes: GLS regressions. Dependent variable: Mental wellbeing (GHQ Caseness score). Reference group: *Male, Single, Not living with a partner, GCSE, Live in Urban area, Owned outright*, and *Employed.* Standard errors (clustered at individual level) in parentheses. † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mortgage		0.27***	0.12**	0.11*	0.12*	0.12*	
		(0.0531)	(0.0481)	(0.0481)	(0.0481)	(0.0481)	
Renting		0.76***	0.33***	0.33***	0.34***	0.34***	
		(0.0698)	(0.0617)	(0.0617)	(0.0619)	(0.0619)	
Employment							
Unemployed		0.54***	0.37***	0.37***	0.37***	0.37***	0.43***
		(0.0473)	(0.0450)	(0.0451)	(0.0451)	(0.0451)	(0.0663)
Self-employed		0.21***	0.22***	0.22***	0.22***	0.22***	0.048
		(0.0603)	(0.0569)	(0.0570)	(0.0570)	(0.0571)	(0.0927)
Household composition							
Aged 0–4		0.024	0.074	0.074	0.075	0.075	
		(0.0511)	(0.0493)	(0.0492)	(0.0492)	(0.0492)	
Aged 5–15		0.062*	0.062*	0.063*	0.062*	0.063*	
		(0.0291)	(0.0273)	(0.0273)	(0.0273)	(0.0273)	
Aged 70 or older		-0.10*	-0.071†	-0.071†	-0.070†	-0.071†	
		(0.0433)	(0.0412)	(0.0412)	(0.0412)	(0.0413)	
Pre-COVID GHQ (Caseness score)			0.38***	0.38***	0.38***	0.38***	
			(0.00825)	(0.00825)	(0.00825)	(0.00825)	
Long-standing illness or impairment			0.48***	0.49***	0.49***	0.49***	
			(0.0414)	(0.0414)	(0.0414)	(0.0414)	
Case per 1,000 people				0.34***	0.33***	0.22†	0.27*
				(0.0443)	(0.0445)	(0.131)	(0.128)
Stringency index				0.0014*	0.0013*	0.0019	0.0014
				(0.000600)	(0.000605)	(0.00220)	(0.00216)
Constant	1.73***	2.01***	1.17***	1.08***	1.12***	1.31***	2.05**
	(0.0277)	(0.125)	(0.115)	(0.117)	(0.152)	(0.300)	(0.669)
Region FE	No	No	No	No	Yes	Yes	Yes
Wave FE	No	No	No	No	No	Yes	Yes
Individual FE	No	No	No	No	No	No	Yes
Observations	117134	111450	109865	109865	109865	109865	117062

Notes: GLS regressions. Dependent variable: Mental wellbeing (GHQ Caseness score). Reference group: *Male, Single, Not living with a partner, GCSE, Live in Urban area, Owned outright*, and *Employed.* Standard errors (clustered at individual level) in parentheses. † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Individuals (cluster)	18617	17454	17141	17141	17141	17141	18609
R^2-*within*	0.016	0.017	0.016	0.018	0.018	0.019	0.019
R^2-*between*	0.005	0.077	0.258	0.259	0.259	0.259	0.001
R^2-*overall*	0.007	0.056	0.182	0.183	0.183	0.184	0.002
Prob. > *F.*	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: GLS regressions. Dependent variable: Mental wellbeing (GHQ Caseness score). Reference group: *Male, Single, Not living with a partner, GCSE, Live in Urban area, Owned outright*, and *Employed.* Standard errors (clustered at individual level) in parentheses. † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

A 10-percentage-point increase in time spent at home (compared to pre-pandemic baseline January 2020) is associated with an average increase of 0.37–0.47 in GHQ Caseness score (which has a standard deviation of 3.35). In standardized terms, a one standard deviation decrease in residential mobility is associated with a 0.066–0.084 standard deviations increase in the GHQ Caseness score. The relationship holds true for GHQ in a Likert scale, albeit slightly weaker (Supplementary Table 2). In general, the relationship between the change in the time spent at home and mental distress is positive – that is, a stay-at-home order predicts worse mental wellbeing. The size of the effect is noticeable and is comparable or higher than the effect of other important observable characteristics, such as unemployment (+ 0.40 points in the GHP Caseness score) or marriage (-0.20 points). We also estimate the impact of lack of mobility on the single components of the GHQ Caseness score (Supplementary Fig. 3). Overall, decreasing mobility worsens all aspects of mental health, and the most noticeable effects are found on the inability to concentrate, to make decisions and to enjoy day to day activities. Interestingly, other aspects, such as feeling worthless and feeling under strain are less affected.

Other independent variables' effects on mental wellbeing follow the literature in the field. Mental health seems to improve for older people and those who live with a partner, while women report on average worse mental health. Mental health also increases for those who are employed and have no pre-existing health conditions. Unsurprisingly, increases in the number of COVID-19 cases and the stringency of restrictive measures worsen mental wellbeing.

Heterogenous Effect Of Lockdown On Mental Health

In Fig. 4, we show how subjective wellbeing (measured as GHQ Caseness score) evolves over time for different socioeconomic and demographic groups identified in the data. Notably, females, children, young adults, single households, and those with a long-term illness have tracked much worse than other groups. Those renting their homes also experienced worse mental health. Nearly all of these groups felt improvements in mental wellbeing between April 2020 and June 2020, which may reflect an adaptation to the "new normal", or public and private policies that improved individual and social wellbeing, or indeed the easing of lockdown measures. There is a notable deterioration of wellbeing around the time the second lockdown starts in England (November 2020), but mental health also improves as the country transitions away from the day when the lockdown was introduced – similar to the evolution after the initial lockdown in March 2020.

In the following two tables (Tables 2 and 3), we interact the change in home duration with a number of different individual characteristics to examine heterogeneity over groups. Recall from Fig. 4 that some groups experienced deeper declines in mental wellbeing – interacting the change in home duration with these variables allows us to demonstrate the kind of person that might be more adversely impacted by mobility restrictions, at least in terms of their effect on mental health. The set of control variables for these regressions with interaction terms are the same as those in Table 1.

Table 2
Interactions with age, gender, marital status, living with partner, and educational attainment

	(1)	(2)	(3)	(4)	(5)
Subjective wellbeing (GHQ): Caseness score	*Age*	*Gender*	*Marital status*	*Living with partner*	*Education*
Δ home duration	0.072***	0.022†	0.042**	0.037**	0.032*
	(0.0135)	(0.0129)	(0.0130)	(0.0129)	(0.0131)
Age*Δ home duration	-0.00070***				
	(0.0000852)				
Female*Δ home duration		0.023***			
		(0.00262)			
Married/civil partnership*Δ home duration			-0.0078*		
			(0.00350)		
Separated/divorced/widowed*Δ home duration			-0.0086†		
			(0.00463)		
Living with partner*Δ home duration				-0.0013	
				(0.00305)	
No qualification*Δ home duration					-0.013†
					(0.00659)
Other qualification*Δ home duration					-0.0096
					(0.00590)
A level*Δ home duration					0.0054
					(0.00436)
Other higher degree*Δ home duration					0.0018
					(0.00474)
Degree*Δ home duration					0.0075†
					(0.00386)
Age	-0.0042†	-0.015***	-0.015***	-0.015***	-0.015***
	(0.00223)	(0.00187)	(0.00187)	(0.00187)	(0.00187)
Female	0.56***	0.21***	0.56***	0.56***	0.55***
	(0.0367)	(0.0523)	(0.0367)	(0.0367)	(0.0367)

Notes: Control variables include *COVID positive*, *living in rural areas*, *housing status*, *employment*, *household composition*, *pre-COVID mental health*, *long-term illness*, *COVID case statistics*, and *stringency index*. Reference group: *Male, Single, Not living with a partner*, and *GCSE.* Standard errors (clustered at individual level) in parentheses. † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

	(1)	(2)	(3)	(4)	(5)
Marital status					
Married/civil partnership	-0.18**	-0.18**	-0.066	-0.18**	-0.18**
	(0.0621)	(0.0622)	(0.0804)	(0.0621)	(0.0621)
Separated/divorced/widowed	-0.00031	-0.0046	0.12	-0.0047	-0.0047
	(0.0753)	(0.0753)	(0.102)	(0.0753)	(0.0753)
Living with partner	-0.21***	-0.21***	-0.21***	-0.20**	-0.21***
	(0.0440)	(0.0440)	(0.0440)	(0.0619)	(0.0440)
Education					
No qualification	-0.32**	-0.31**	-0.31**	-0.31**	-0.13
	(0.0978)	(0.0978)	(0.0978)	(0.0978)	(0.137)
Other qualification	-0.13	-0.13	-0.13	-0.13	0.0089
	(0.0803)	(0.0803)	(0.0802)	(0.0802)	(0.118)
A level	0.00072	-0.0021	-0.00023	-0.00082	-0.080
	(0.0596)	(0.0596)	(0.0596)	(0.0596)	(0.0864)
Other higher degree	0.093	0.091	0.092	0.092	0.065
	(0.0652)	(0.0652)	(0.0652)	(0.0652)	(0.0935)
Degree	0.20***	0.20***	0.20***	0.20***	0.084
	(0.0538)	(0.0539)	(0.0538)	(0.0538)	(0.0772)
Constant	0.53†	1.31***	1.01***	1.08***	1.29***
	(0.307)	(0.301)	(0.303)	(0.301)	(0.305)
Control	Yes	Yes	Yes	Yes	Yes
Region fixed-effects	Yes	Yes	Yes	Yes	Yes
Wave fixed-effects	Yes	Yes	Yes	Yes	Yes
N	109865	109865	109865	109865	109865
N (cluster)	17141	17141	17141	17141	17141
R^2*-within*	0.020	0.020	0.019	0.019	0.019
R^2*-between*	0.259	0.259	0.259	0.259	0.259
R^2*-overall*	0.184	0.184	0.184	0.184	0.184
Prob. > *F.*	0.000	0.000	0.000	0.000	0.000

Notes: Control variables include *COVID positive*, *living in rural areas*, *housing status*, *employment*, *household composition*, *pre-COVID mental health*, *long-term illness*, *COVID case statistics*, and *stringency index*. Reference group: *Male, Single, Not living with a partner*, and *GCSE.* Standard errors (clustered at individual level) in parentheses. † $p < .10$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 3
Interactions with urbanity, home ownership, employment status, and other health conditions

	(6)	(7)	(8)	(9)	(10)
Subjective wellbeing (GHQ): Caseness score	*Live in rural area*	*Home ownership*	*Employment status*	*Pre-existing mental health*	*Long-term illness*
Δ home duration	0.037**	0.031*	0.040**	0.040**	0.043***
	(0.0128)	(0.0129)	(0.0128)	(0.0128)	(0.0128)
Live in rural area*Δ home duration	-0.0081**				
	(0.00301)				
Mortgage*Δ home duration		0.014***			
		(0.00287)			
Renting*Δ home duration		0.0012			
		(0.00408)			
Unemployed*Δ home duration			-0.012***		
			(0.00280)		
Self-employed*Δ home duration			0.0041		
			(0.00479)		
Pre-COVID GHQ (Caseness score)*Δ home duration				-0.0014*	
				(0.000566)	
Long-standing illness*Δ home duration					-0.018***
					(0.00289)
Live in rural area	0.070	-0.047	-0.047	-0.046	-0.046
	(0.0589)	(0.0420)	(0.0420)	(0.0420)	(0.0420)
Mortgage	0.12*	-0.090	0.12*	0.12*	0.12*
	(0.0481)	(0.0627)	(0.0481)	(0.0481)	(0.0481)
Renting	0.34***	0.32***	0.34***	0.34***	0.34***
	(0.0619)	(0.0873)	(0.0618)	(0.0618)	(0.0618)
Unemployed	0.37***	0.37***	0.53***	0.37***	0.37***
	(0.0451)	(0.0451)	(0.0599)	(0.0451)	(0.0451)
Self-employed	0.22***	0.22***	0.16†	0.22***	0.22***
	(0.0571)	(0.0571)	(0.0889)	(0.0570)	(0.0571)
Pre-COVID GHQ (Caseness)	0.38***	0.38***	0.38***	0.40***	0.38***
	(0.00825)	(0.00825)	(0.00825)	(0.0121)	(0.00825)
Long-standing illness or impairment	0.48***	0.48***	0.48***	0.48***	0.75***

	(6)	(7)	(8)	(9)	(10)
	(0.0414)	(0.0414)	(0.0414)	(0.0414)	(0.0587)
Constant	1.08***	1.17***	1.03***	1.04***	0.99***
	(0.301)	(0.302)	(0.301)	(0.300)	(0.300)
Control	Yes	Yes	Yes	Yes	Yes
Region fixed-effects	Yes	Yes	Yes	Yes	Yes
Wave fixed-effects	Yes	Yes	Yes	Yes	Yes
N	109865	109865	109865	109865	109865
N (cluster)	17141	17141	17141	17141	17141
R^2-*within*	0.019	0.020	0.019	0.019	0.020
R^2-*between*	0.259	0.259	0.259	0.259	0.259
R^2-*overall*	0.184	0.184	0.184	0.184	0.184
Prob. > *F.*	0.000	0.000	0.000	0.000	0.000

In Table 2, the own-effect of the change in mobility is consistently positive, although lacking in statistical significance when we interact it with the gender of the respondent (Column 2). The interaction with the female variable, however, shows that women suffered more than men over the period. Older respondents and those who were partnered were more resilient (Columns 1, 3, and 4). Finally, more educated individuals suffered more (Column 5).

For ease of interpretation, we also graphically represent the estimation results of Table 2 in Fig. 5. For almost the entire range of the percentage change in time spent at home, women are worse off than men. The gradient is also consistent for the interaction with age: the larger the change in home duration, the worse off people are, but this relationship is much stronger for younger people than for older people.

In Table 3, we continue with the interactions of the change in time spent at home with the following independent variables: living in an urban area, homeownership, employment status, a measure of pre-existing mental health (pre-COVID), and an indicator for having a long-term illness. Those living in rural areas, the unemployed, and those who had a long-term illness before COVID-19 started are less affected by the change in mobility. Similarly, individuals with better pre-pandemic mental health suffered more from restrictions to mobility.

Similar to Fig. 5, we also graphically represent these results in Fig. 6. Those who are paying off a mortgage and renting – perhaps because of increased financial pressure – show a larger deterioration in their mental health than those who own their domicile (Fig. 6a). The self-employed are also more adversely affected than those who are employed, and the unemployed are hardly affected at all (Fig. 6b). Across the range of the change in home duration, the effect of restrictions to mobility on mental health is less for those who have previous mental health issues or long-term illness (Figs. 6c and 6d).

In Fig. 7, we graphically represent the estimated coefficients on three-way interactions of mobility, gender, and age group (Fig. 7a) and mobility, gender, and an indicator for having a child aged 5–15 in the household (Fig. 7b). Younger women are more adversely affected than younger men, although the size of the differential declines as we move to older age groups. In addition, having a child in the household amplifies the negative relationship between mental health and being female during periods of increased mobility restrictions.

These estimates show how changes in average mobility impact the *average* mental health outcome. The main limitation of this approach is that, especially when we interpret interaction effects, the underlying assumption is that the movement change is of the same magnitude for the whole population. This is unlikely to be the case, as older people or people with long term illnesses

were less mobile even before the pandemic started. Therefore, caution should be used when interpreting these estimates, as this type of measurement error could create attenuation bias in the results, which could overestimate the effects for groups of individuals whose movement change is less than the population average, and underestimate the effects for those whose mobility was higher.

However, the negative impact of lack of mobility may arise from several sources apart from restrictions to individuals' movement. For example, it is possible that the lack of mobility in society, which is in turn reflected in a decrease of available services and overall social interaction, may have a negative impact on individual wellbeing, in addition to the effects due to the restrictions on the individual mobility.

[3] We obtain robust and qualitatively similar results when we 1) cluster the standard errors at the household level, 2) use a subsample of individuals who completed all nine COVID-19 waves (40.5% of the full sample) or 3) exclude those subjects who did not participate in the latest pre-COVID wave (wave 10 in 2019; 5.72% of the full sample).

Discussion

The results of this study have considerable implications for the management of the current and future pandemics. Since the start of the pandemic, evidence regarding the adverse impact of lockdowns on subjective wellbeing has accumulated in the scientific literature, including the current study. Although the evidence that lockdowns suppress the transmission of the disease is clear, it must be balanced against the real costs associated with mental health deterioration when physical human contact is limited via mobility restrictions.

In our study, we combined a robust measure of mental health – the GHQ Caseness score – with data from Google on mobility restrictions to track how mental wellbeing evolved during periods of lockdown and easing of restrictions in the UK. We demonstrated that the decline in mental health is significant, and that certain groups experienced significantly sharper deteriorations in mental health than others. Particularly noteworthy are the gender-based differences: women suffer more from mobility restrictions than men, and this is especially pronounced if there are small children in the household, perhaps reflecting the increased burden of domestic or at-home childcare faced by women when schools pivot to remote learning. Households that are relatively more financially insecure are also at risk for further mental health distress, as well as those who are not partnered and may not have someone with whom to share the burdens of lockdown.

From a policy perspective – when lockdowns are unavoidable – it makes sense to attempt to limit the decline in mental health for the population under lockdown. Governments can invest in capacity to manage deteriorating mental health via increased funding for psychological support and counselling through telemedicine or online consultations, as well as the increased guarantee of job security and the provision of financial aid when people are unable to work. Schools can remain open for as long as possible to allow parents to both work at home without having to attend to childcare and to reduce the disruption in student learning, which may have longer-term impacts over the life course of the child and the mental wellbeing of the parents.

Moreover, as Snowden (53) points out in his historical overview of pandemics, "major epidemics caught authorities unprepared, leading to confusion, chaos, and improvision" (p. 77). Under such circumstances, policy indicators via survey data are often not fast enough to guide effective responses. By the time such data are generated, decisions are already made that can have long-lasting effects on society. The push towards Big Data allows the use of high-frequency data in the policy realm (54). In addition to helpline call volume data (40), real time mobility data as an information source also provides a good general indicator for the state of public mental health during a pandemic, which can be added to the toolset of ambient and passive sensing wellbeing monitoring (55–60). Although such high-frequency data are not fine-grained enough for some purposes, the relationship observed here provides encouragement for further consideration of tapping into various sources of high-frequency data to make informed policy decisions. In times of crisis where lagged availability can produce societal costs, it is particularly important for decision makers to remain open and consider information that can be gathered from alternative measures to improve the agility and adaptiveness of policy responses.

Materials And Methods

Understanding Society (UK Household Longitudinal Study).

We use data from the UK Household Longitudinal Study (UKHLS), now known as Understanding Society. UKHLS surveyed approximately 40,000 households living in the United Kingdom in Wave 1. The survey contains a wide range of questions on social, economic, and behavioural issues. Respondents lived in 12 Government Office Regions across the UK (NUTS level 1: nine English regions,3F3F[4] Scotland, Wales, and Northern Ireland). Data collection started in 2009–2010 for Wave 1; ten waves are currently available. Wave 10 (pre-COVID-19) consists of individuals surveyed during the period 2018–2019.

On April 2020, selected respondents of the Understanding Society were invited to take part in the first wave of a new COVID-19 special survey, which consisted of important questions on the impact of the pandemic on the wellbeing of individuals, families, and wider communities, including information about caring responsibilities and family life, employment and financial situation, financial wellbeing, home schooling, and mental wellbeing. Participants were asked to complete one survey per month until July 2020, followed by a survey every two months from September 2020 in order to track changes in their circumstances and environments. 17,452 individuals completed a full post-COVID-19 survey in April 2020 (61). Supplementary Table 1 presents basic descriptive statistics of the estimation sample.

Our analysis is based on Wave 10 of the regular Understanding Society and the nine waves4F4F[5] of the Understanding Society COVID-19 special survey. The final estimation sample consists of 110,008 (individual×wave) observations, with 19,763 individuals from 13,295 households. Thus, the analysis below covers the period of the initial lockdown as well as the series of repeated lockdowns all the way until one and a half years into the pandemic – from March 2020 to September 2021.

Mental health was measured in Understanding Society using the General Health Questionnaire (GHQ) Caseness score (62-63). The GHQ is regarded as one of the most reliable indicators of psychological distress or “disutility” (64-65, see Supplementary Note 1 for question wordings). The GHQ Caseness score is constructed from responses to 12 questions covering feelings of strain, depression, inability to cope, anxiety-based insomnia and lack of confidence (see the Appendix for details). The twelve answers are summed up into a GHQ Caseness score that indicates the level of mental distress, resulting in a scale from 0 (the least distressed) to 12 (the most distressed).

Google’s Community Mobility Reports

The impact of the UK’s series of lockdowns on mobility is measured using movement information collected by Google from internet-connected devices with the “location history” setting turned on. The information is anonymised and a person cannot be identified from the resulting datasets called Community Mobility Reports.5F5F[6] These reports are provided by Google to the public, partly to assist in crafting policies that can help limit the spread of SARS-CoV-2. For our analysis, we focus on the mobility measure relating to time spent in residential places, i.e., changes in length of stay at home compared to the pre-COVID-19 baseline, which is the median value of the corresponding day of the week between the 3rd January to 6th February 2020. While the Google Mobility Reports measure is on a refined geographical level (i.e., nomenclature of territorial units for statistics (NUTS) level 3), the location information of the Understanding Society survey participants is only available on the NUTS level 1 (or major socio-economic regions). Thus, in order to merge the two datasets, we aggregate the NUTS level 3 mobility to the 12 Government Office Regions by taking the average mobility measure weighted by the population of the subregions. We show the average monthly changes in residential mobility across the 12 regions in the UK in Supplementary Fig. 1. We observe that London dwellers had the largest decrease in mobility at the beginning of the pandemic (i.e., April 2020), as the duration of staying home increased by approximately 30% compared to the January 2020 baseline. For subsequent analysis, we calculate, for each participant, the average mobility change in the past 7 (or 14) days from the date when the survey was conducted.

COVID Statistics and Government Stringency

We use data on cases and death due to COVID-19 obtained from the UK Health Security Agency, which are reported up to the level of the 12 regions: North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales, Scotland, and Northern Ireland. This information is combined with the population to calculate the reported case per thousand people at the regional level. Thus, in our study, we are also able to control for the

severity of COVID-19 in the region, which allows us to account for the changes in mental health associated with the prevalence of COVID-19 within a region, similar to how Brodeur et al. (10) used lagged COVID-19-related deaths.

We use the COVID-19 Stringency Index from the Oxford Coronavirus Government Response Tracker (OxCGRT) to proxy the strictness of lockdown policies implemented by the government (66). The stringency index is a composite measure constructed from nine policy indicators (e.g., workplace closures; restrictions on public gatherings; closures of public transport; stay-at-home requirements) and is reported at the UK country levels (England, Scotland, Wales, and Northern Ireland, see Supplementary Fig. 2 for the development of Stringency Index over February 2020 to September 2021 across the four countries). Similar to the mobility measure, we calculate the past 7-day (or 14-day) average of COVID-19 case statistics and stringency index from the date the survey was conducted.

Summary statistics are presented in Supplementary Table 1.

Estimation Strategy

We model mental health – measured using the GHQ Caseness score – as a function of the change in the duration spent at home, socioeconomic and demographic characteristics, mental health stock before the pandemic, COVID-19 prevalence in the community, time-invariant region and individual fixed effects, as well as period fixed effects. More explicitly, we estimate variations of the following regression equation:

$$GHQ_{it} = \alpha + \beta(\Delta home)_{rt} + \boldsymbol{\gamma}'\mathbf{X}_{it} + \varepsilon_{it},$$

where i and t are individual and wave indexes, respectively, $(\Delta home)_{rt}$ is the past 7-day average of the percentage change in time spent at home compared to the pre-pandemic baseline period in region r at the time of survey t, $\mathbf{X}_{it}$ is a vector of control variables as described previously, and ε_{it} is the error term. The parameters α, β, and vector of parameters $\boldsymbol{\gamma}$ are estimated via generalised least squares. For statistical inference, the standard errors are clustered at the individual level (although clustering by region and wave does not change our conclusions). The parameter of interest is β, which quantifies the relationship between the GHQ Caseness score and the change in the duration of time spent at home.

To demonstrate the stability of the estimated coefficient, we progressively expand the set of control variables entering $\mathbf{X}_{it}$. After the bivariate regression between GHQ and change in home time, we first include a set of socioeconomic and demographic characteristics, such as gender, marital status, educational attainment, household composition (having children of various ages), home-ownership status (or renting), urban area, and employment status. Information on marital status, educational attainment, urban area, and home-ownership status are from the pre-COVID-19 wave. Second, we include a measure of mental health stock using pre-COVID-19 GHQ Caseness score as a proxy, and we control for whether the individual has a long-standing (or chronic) illness. Third, we incorporate the prevalence of COVID-19 in the community by including the number of cases per 1,000 people as well as an index of the stringency of the lockdown. Finally, we include various fixed effects in the regression: region-specific, individual-specific, and wave-specific fixed effects. These are intended to capture unspecific features or unvarying characteristics of individuals, regions, and the survey waves. As an extension, we explore the heterogeneity of the relationship by interacting the change in home duration with the control variables.

[4] East of England, East Midlands, London, North East, North West, South East, South West, West Midlands, and Yorkshire and the Humber.
[5] April, May, June, July, September, and November 2020, and January, March, and September 2021.
[6] For more information, see Google's website for the Community Mobility Reports: https://www.google.com/covid19/mobility/.

Declarations

Author Contributions: H.F.C., Z.C., S.M., A.R.P., M.T., D.P., D.A.S., and B.T conceived the project. H.F.C. and S.M. collected the data. H.F.C. performed the analysis. H.F.C., S.M., A.R.P., and B.T. interpreted the results. H.F.C., S.M., A.R.P., M.T., D.P., and B.T. wrote the manuscript. H.F.C., Z.C., S.M., A.R.P., M.T., D.P., and B.T. edited the manuscript.

Competing Interest Statement: The authors declare no competing interests

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Data availability

Data from the Understanding Society are available through the UK Data Service, providing granted research access (Institute for Social and Economic Research, 2022). Mobility data were downloaded from Google's COVID-19 Community Mobility Report. UK COVID-19 epidemiological data were collect-ed from the UK Health Security Agency. Subnational UK COVID-19 Stringency Index were obtained from the Oxford Coronavirus Government Response Tracker (OxCGRT). Code used to analyze data and generate results are available from OSF https://osf.io/hg6e4/.

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Supplementary Information

The Supplementary Information is not available with this version

Figures

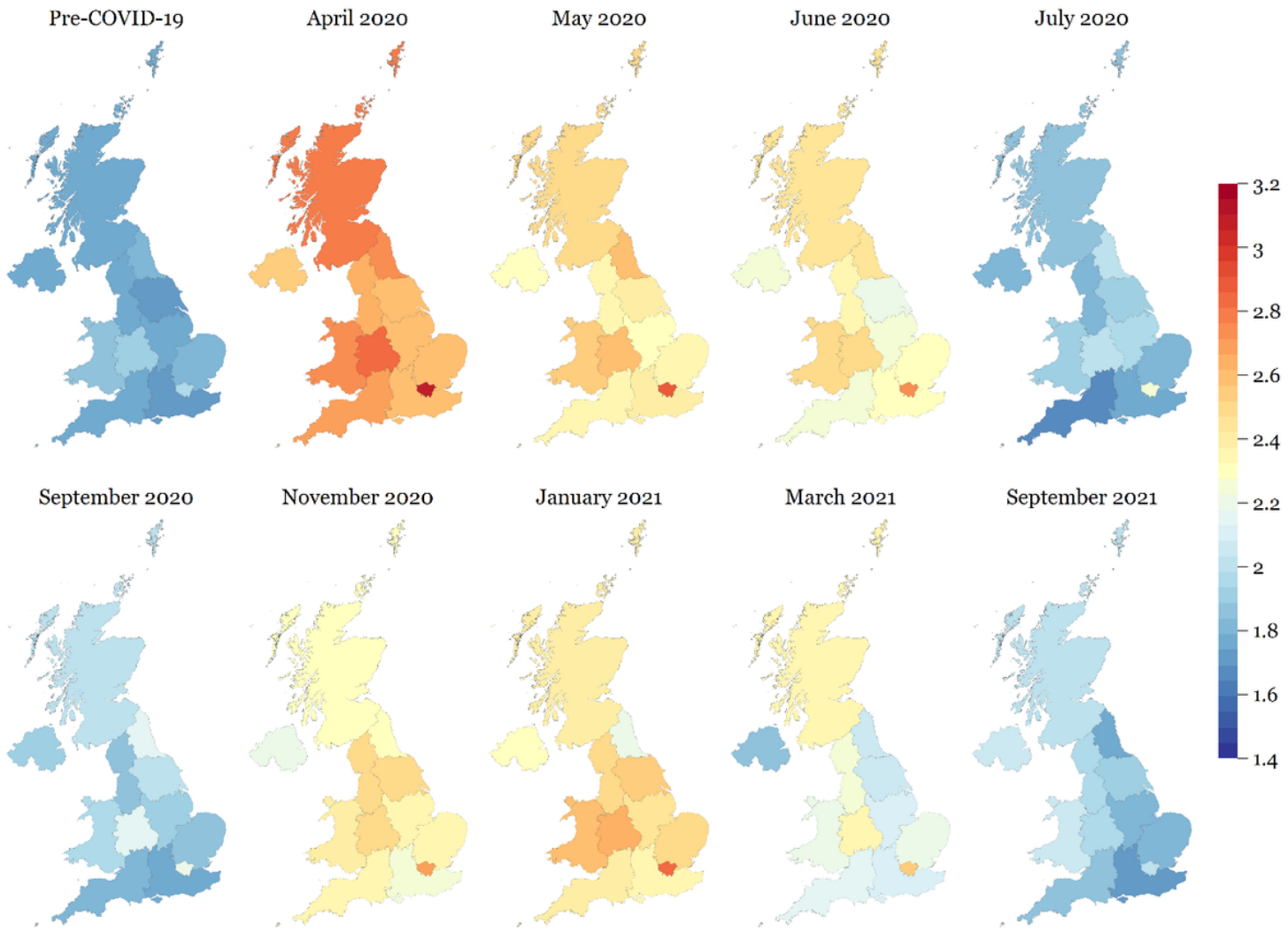

Figure 1

Mental health (GHQ Caseness score) across UK regions over time

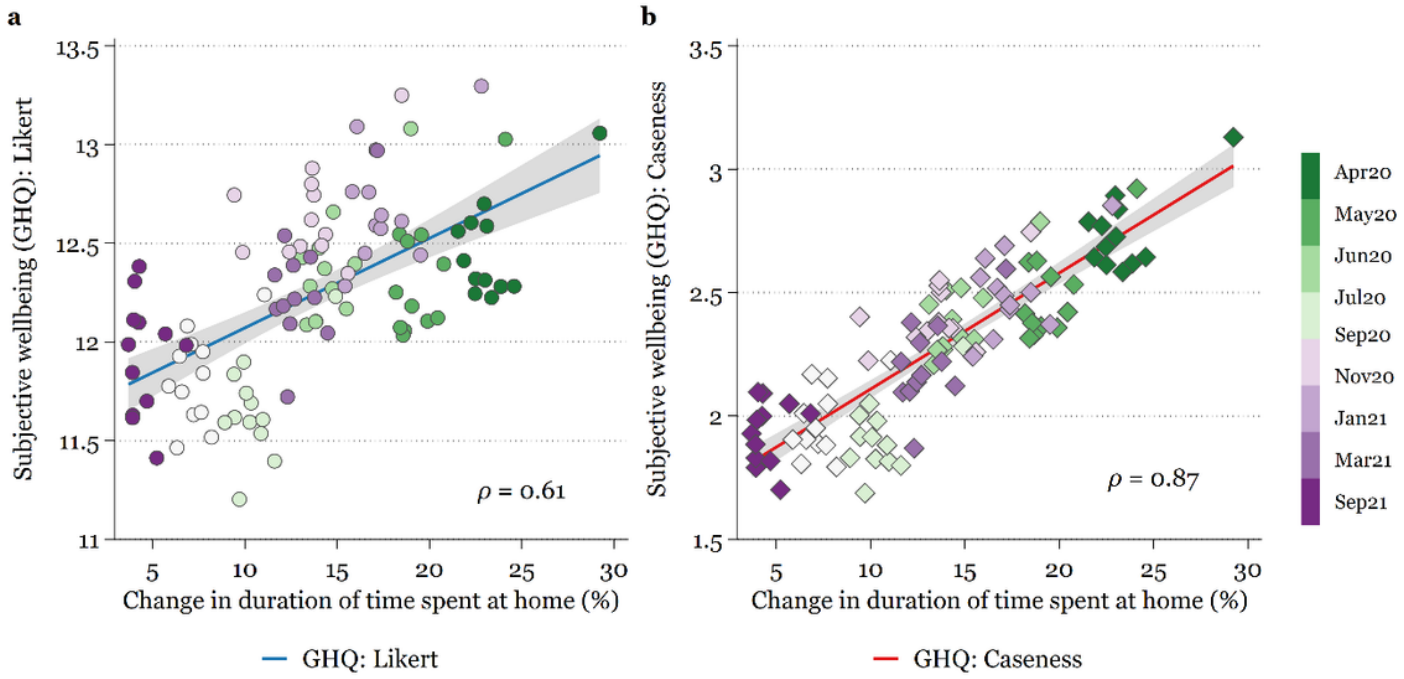

Figure 2

Mental health and mobility. Correlation between mobility and GHQ measures (A, GHQ likert, and A, GHQ Caseness) are monthly averages (9-wave) for each 12 regions. Marker colours represent the nine COVID-19 survey waves – earlier waves appear in green and later waves appear in purple. Shaded areas represent 95% confidence intervals of the linear fit.

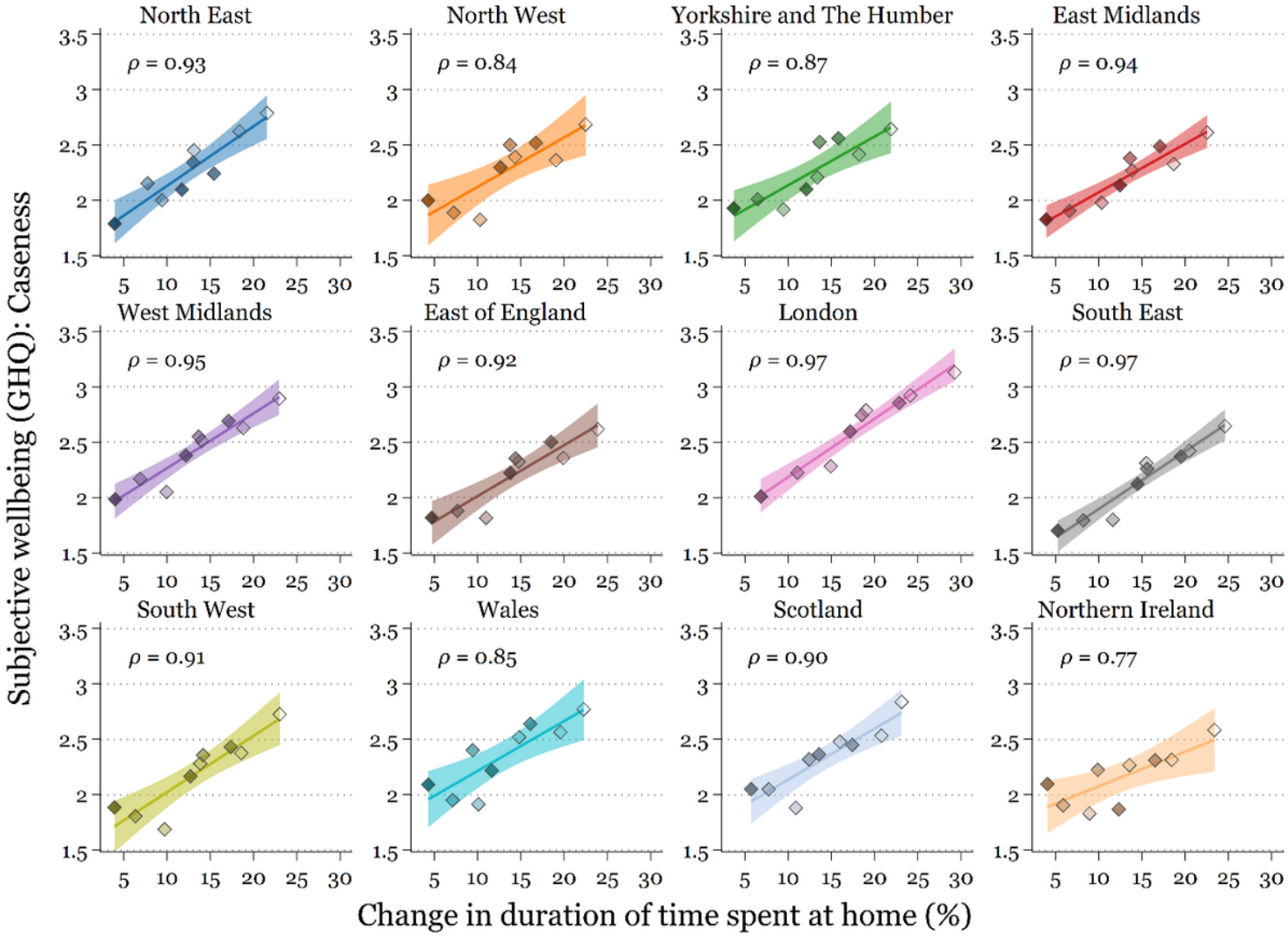

Figure 3

Relationship between GHQ Caseness score and mobility within region. Mental health (GHQ) is averaged over each survey wave for each UK region. Markers with darker colour represent later waves. Shaded areas represent 95% confidence intervals of the linear fit.

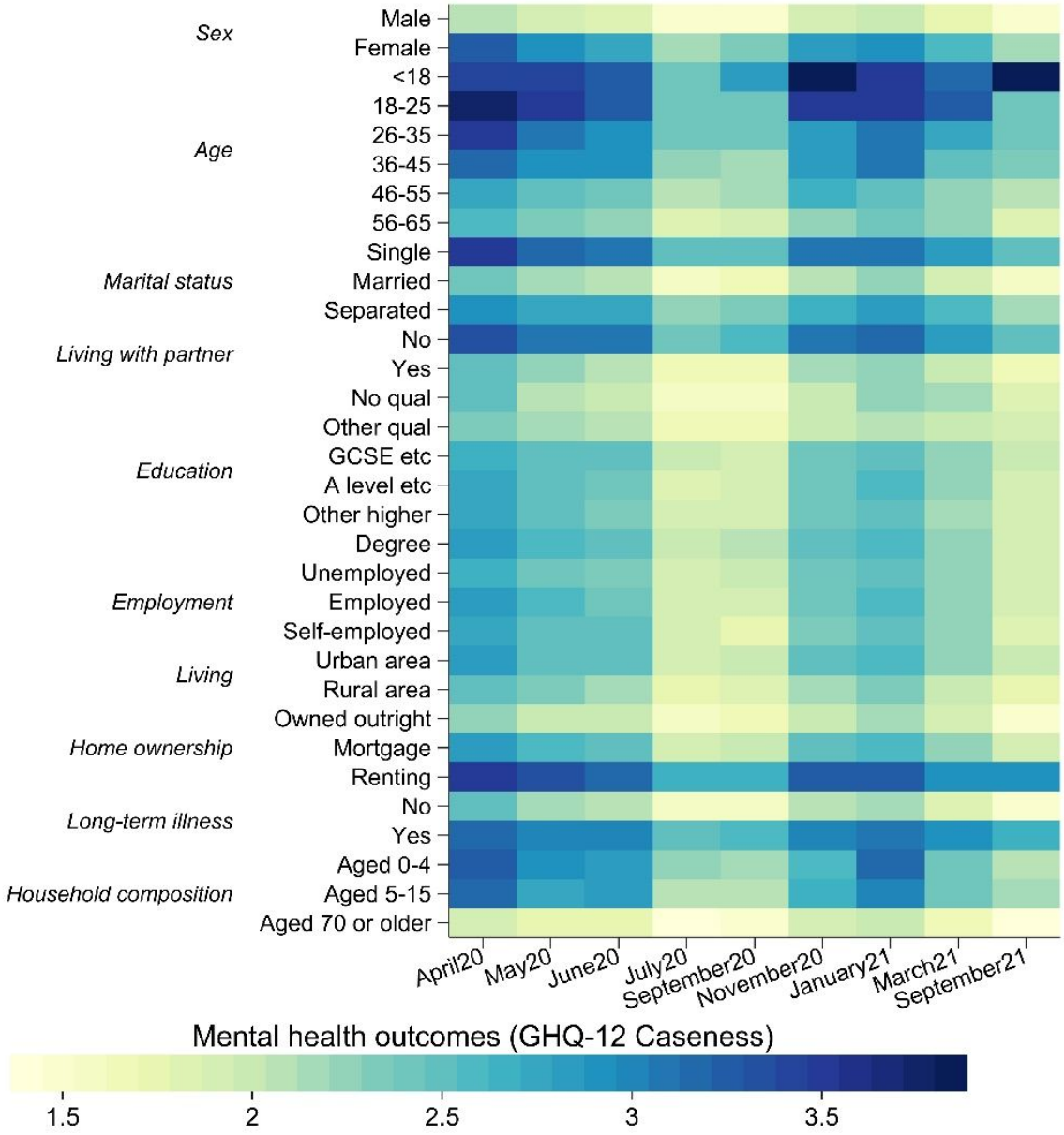

Figure 4

Mental health across different groups over time. Individual GHQ Caseness scores are averaged within groups across the nine waves of Understanding Society survey.

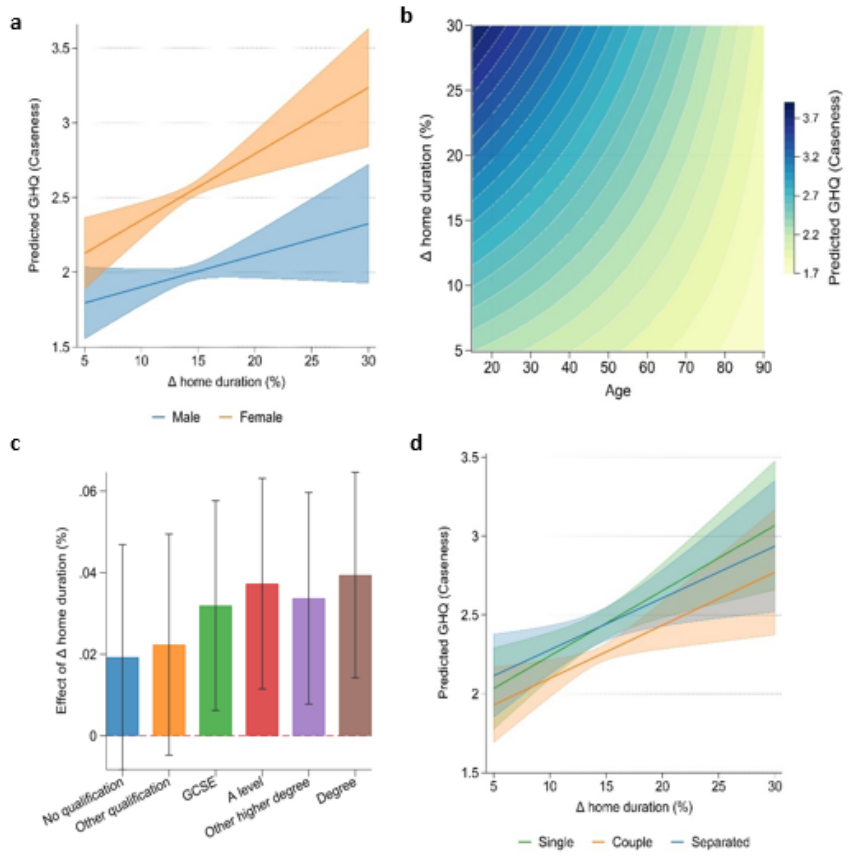

Figure 5

Heterogenous effect of lockdown on mental health across (A) gender, (B) age, (C) education, and (D) marital status groups. Estimated heterogenous effect of lockdown on mental health across groups were obtained from regression results in Table 2. Error bars (C) and shared area (A and D) represent 95% confidence intervals.

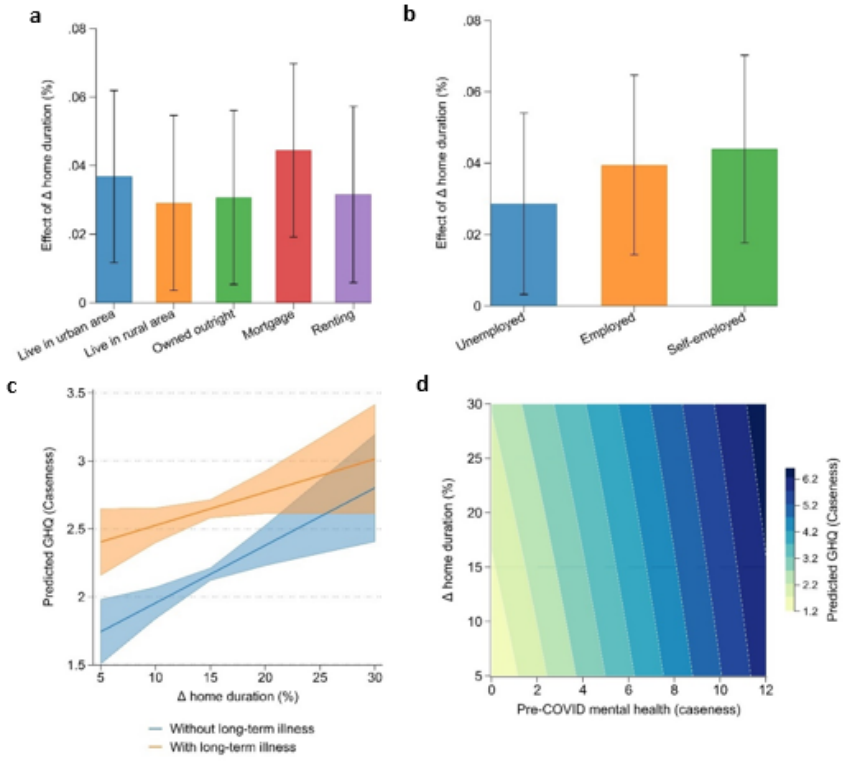

Figure 6

Heterogenous effect of lockdown on mental health across (A) homeownership and living area, (B) employment status during COVID-19, (C) long-standing illness or impairment, (D) pre-existing mental health issue groups. Estimated heterogenous effect of lockdown on mental health across groups were obtained from regression results in Table 3. Error bars (in panels a and b) and shared area (panel c) represent 95% confidence intervals.

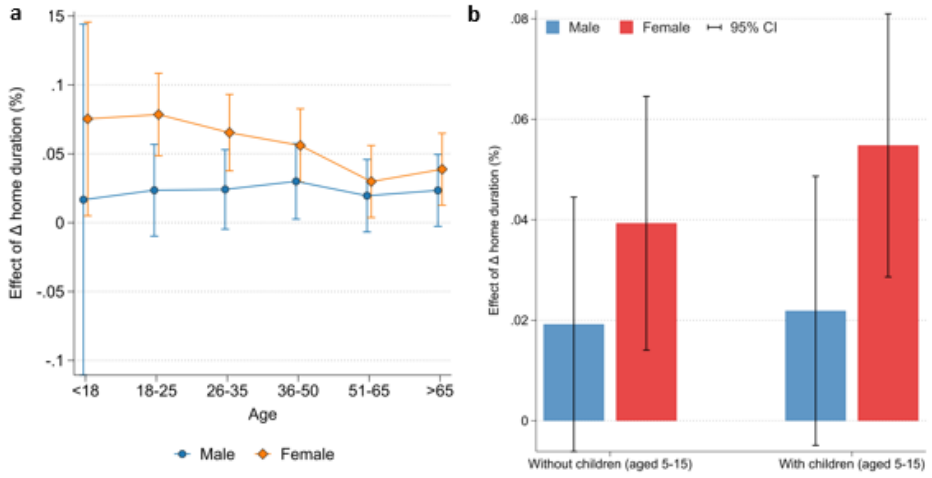

Figure 7

Three-way interaction of mobility, sex, and age group (A) and mobility, sex, and having a child aged 5–15 in the household (B). Error bars represent 95% confidence intervals.