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DISCUSSION PAPER

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Keywords: long-term sickness, economic inactivity, coronavirus pandemic, proxy responses, survey methodology, household surveys, survey methods

JEL classification: C83, C81, J21

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1. Introduction

There has been a considerable increase in the number of people in the UK reporting that they are economically inactive due to long-term sickness or disability (henceforth "long-term sickness") since the coronavirus pandemic. This apparent rise in the number of people who are long-term sick has generated considerable research and policy interest (Health Foundation 2024, Ray-Chaudhuri and Waters 2024, OBR 2023, House of Lords Economic Affairs Committee 2022, Haskel and Martin 2022). The key data source underpinning this discussion is the long-running Labour Force Survey (LFS), run by the Office for National Statistics (ONS).

However, it remains unclear how much of the rise in long-term sickness is a genuine phenomenon, and how much it is a methodological artefact. To date, two main concerns have been raised. Firstly, LFS response rates have sharply fallen, and employment estimates from the LFS appear to diverge from HMRC payroll data over recent years, suggesting that LFS data may have under-estimated employment and over-estimated inactivity for a time (Corlett 2024). Secondly, the rise in self-reported long-term sickness may be driven by changes in reporting behaviour. Rising long-term sickness coexists with falling inactivity due to 'looking after the family/home' (OBR, 2023, Box 2.3), which may reflect underlying changes in the causes of inactivity, but may equally reflect changing social norms around the reporting of sickness (notably mental health) or the reasons for economic inactivity. It could also reflect an increase in individuals being categorised as sick or disabled by other state systems, e.g. welfare (OBR, 2023), influencing responses to more subjective questions on the LFS.

We contribute to this debate by exploring two other, previously unexamined methodological issues which could influence trends – proxy responses and survey mode/wave. Firstly, proxy responses are responses by one individual about another. Not only are these allowed in LFS (unlike some other surveys), but they account for a substantial share of responses, particularly for young people, as we show below. Moreover, proxy responses might be linked to reporting of long-term sickness because these types of response differ from personal responses in social desirability pressures, and also because proxy respondents may have imperfect knowledge of the person in question. Secondly, before the coronavirus pandemic, LFS headline results combine face-to-face interviews at wave 1, with follow-up telephone interviews in the following four quarters (waves 2-5). Not only did survey mode for wave 1 data temporarily change to telephone during the pandemic, but the falling response rates are much more noticeable for waves 2-5. It may be the case that the trends restricted to looking at a consistent mode (face-to-face) – which also has noticeably higher response rates – may show different trends.

Given longstanding concerns about the LFS, as well as the potential to save money through online-first approaches, ONS are moving towards the 'Transformed Labour Force Survey' (TLFS). However, this has been much-delayed due to operational challenges, and is currently scheduled to take place in 2027,[1] with many methodological choices still under discussion – hence this is a moment of particular importance to scrutinise the LFS.

[1] This has been a long time in development; it is first mentioned as early as 2014 (see LFS User Guide volume 1, section 3.4.3), and the first published tests of this approach include data collection in 2018 https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/methodologies/labourmarketsurveyresearchandresultsoverview. The latest update at time of writing is available from https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/labourmarkettransformationupdateonprogressandplans/december2024

Using new analyses of LFS microdata, our paper has three aims. First, to test whether the apparent rise in long-term sickness in the LFS is robust to inclusion or exclusion of proxy responses and survey mode/wave. Second, to raise awareness of these methodological issues on the LFS, and so support other researchers using the LFS. Third, more broadly, to draw attention to the methodological dimensions of key economic statistics, and the need for economic analysts to pay attention to issues of measurement.

We find that proxy responses accounts for a surprisingly large 40% of LFS data for ages 16-64, rising to over 80% for 16-24 year olds. These rates have increased since pre-pandemic levels, reflecting an important but under-explored change in the LFS data. Proxy rates are systematically different across personal characteristics: higher for people who are younger (and the very old), male, working full-time, economically inactive due to being a student, and who do not have long-term health conditions. Personal responses, in contrast, are higher for people with long-term health conditions.

We find that the increase in long-term sickness (which we define in various ways to test robustness) since the pandemic may be slightly smaller when accounting for changes in response patterns, but clearly still increases across various cuts of the LFS data, including if we focus only on personal responses or wave 1 data. Personal responses show a larger and more sustained increase in rates of long-term sickness than proxy responses. It seems clear that the increase in reported long-term sickness is not simply a methodological artefact, though the degree of increase is somewhat less clear.

There is a complex interplay between health, employment status, and response type on the LFS, which complicates our ability to disentangle causal effects. To shed some light on these inter-relationships, we present analysis using the longitudinal two-quarter LFS, from which we can observe the same person across multiple waves who have different response types. We find that people who respond first via proxy and then via personal response have a greater likelihood of 'acquiring' a long-term health condition than people who give personal responses in both quarters, and this holds even if they remain employed between quarters. This suggests some systematic bias in under-reporting long-term health conditions by proxy responders. This bias appears to have increased since the pandemic, though the opposite switching ('losing' a health condition) has also increased, which may point to less agreement on what constitutes a long-term health condition over recent years.

Taken together, our findings suggest that the increases in self-reported long-term health conditions and inactivity due to long-term sickness are robust to various aspects of LFS methodology, which should increase confidence in the trends. However, the LFS is not designed to robustly track health trends, and the measures we use are self-perceptions of illness categories and work-limiting disability rather than more detailed health measures.[2] Nonetheless, even an increase in *perceived* ill-health is important for public policy.

We also do not present evidence on LFS data quality more generally, although the striking increase in the prevalence of proxy responses might suggest a deterioration in reliability of the LFS data all else equal. Data for young people is dominated by proxy responses (most likely from their parents), which may suggest particular caution in interpreting these data.

The paper proceeds as follows. Section 2 briefly describes the literature in two areas: the impact of survey mode, response rate and proxy responses; and recent trends in sickness

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[2] One of the authors will present evidence on this from other surveys in a forthcoming briefing paper by Henking & Geiger, to be published by the Centre for Society & Mental Health (CSMH) in summer 2026 – see https://www.kcl.ac.uk/csmh

and inactivity in the UK, especially based on the LFS. Section 3 briefly documents LFS methods, and how these have changed in recent years in response to the pandemic. Section 4 examines trends and patterns in proxy responses on the LFS. Section 5 explores the robustness of trends in sickness and inactivity rates to different approaches. Section 6 concludes and provides recommendations for economic measurement.

2. Literature

Trends in sickness and inactivity

There has been a proliferation of analysis on the increase in economic inactivity and long-term sickness in the years since the coronavirus pandemic. Most of this work has relied on the LFS. Initial work noted the sustained increase in economic inactivity rates in the UK, which became more evident in early 2022 once the immediate impact of the coronavirus pandemic subsided. The increase in economic inactivity was often decomposed into changes by “main reason” and age group using the LFS, revealing the concurrent increase in “long-term sickness” as the main reason given for economic inactivity (IFS, 2022a; Tinson et al., 2022; House of Lords Economic Affairs Committee, 2022; IFS, 2023; Murphy and Thwaites, 2023). Haskel and Martin (2022) explored the role of long-term sickness in more detail, highlighting a range of measures of long-term sickness available from the LFS, and the effects of long-term sickness on macroeconomic outcomes.

Importantly, IFS (2022b) documented that while there were rises in inactivity due to long-term sickness, these were not due to increased outflows from employment to inactivity. This suggests that the increase in long-term sickness was not directly causing the increase in inactivity, but happening alongside it. Put another way, the increase in rates of inactivity with long-term sickness as the main reason may have been due to changing reporting behaviour amongst the inactive population, or changing flows rates for different types of economically inactive people. Meanwhile, what increase in outflows from employment were observed were instead associated with early retirement, which may have been associated with wealth effects or behavioural change.

Most of this literature looks at potential explanations for rising long-term sickness in the UK. One hypothesis for the increase in health-related inactivity was Long COVID – the ongoing symptoms after a COVID-19 infection. While many people reported Long COVID symptoms (over 2 million people at peak based on ONS figures), the degree of severity varied. Moreover, some of the people experiencing Long Covid were not working beforehand, so while this may have seriously impacted their lives, Long COVID among this group would not lead to declines in employment. Estimates of the increase in inactivity due to Long COVID vary from close to 100,000 for cumulative exits in mid-2022 based on top-down modelling (Reuschke and Houston, 2023; Haskel and Martin, 2022) to 27,000 for point-in-time exits based on a longitudinal person-level study (Ayoubkhani et al., 2024). Either way, these numbers are much smaller than the increase of around 750,000 in inactivity due to long-term sickness (470,000 for total inactivity). The rise in self-reported long-term sickness on the LFS is also disproportionately in younger people and associated with mental health conditions, which are largely inconsistent with Long COVID impacts. This suggests that Long COVID is a small contributor to the increase in economic inactivity and long-term sickness.

Another explanation relates to demographics. Some increase in inactivity rates would have been expected over recent years, given demographic effects. Boys (2022) calculates the effect of population aging on inactivity rates in the UK, and finds that the demographic effect on the 16 to 64 year old population between 2019 and 2022 Q2 can explain almost half of the observed increase in inactivity rate over this period. ONS (2023a) also conduct an analysis of the role of changing demographics on inactivity rates in the UK, and find that demographic change can explain over half (59%) of the change in inactivity rates between Quarter 3 2019 and Quarter 3 2022. Some of this demographics-driven aging would likely be expected to increase aggregate rates of long-term sickness, given high prevalence of long-term health conditions at older ages. Nonetheless, increases in self-reported health conditions within age groups cannot be explained by demographics, and ONS (2023a) also find a much larger increase in inactivity due to long-term sickness or disability than would have been expected from demographic effects alone.

A different approach to understanding UK trends is to compare the UK experience to other countries – particularly as the UK appears unusual relative to other advanced economies in this regard. While the inactivity rate rose during the coronavirus pandemic nearly everywhere, it then fell back to trend in 2021 and 2022 in most OECD countries (Burn-Murdoch, 2022), but the UK saw a more gradual increase that was then sustained beyond 2022. Explanations for the unusual UK experience include health effects (Haskel, 2022; Burn-Murdoch, 2022; ONS, 2022a; Murphy and Thwaites, 2023) and behavioural effects (ONS 2022b). By contrast, Favilukis and Li (2023) argue that the decrease in participation rates in the US during the pandemic was due to the wealth effects of the house price growth.

What nearly all of these studies have in common is that the LFS data are central. However, the quality and validity of the LFS data remains underexplored, which is our focus here.

Methodological impacts on economic data

It is not always understood that the LFS combines in-person interviews with those that are conducted by telephone, and the balance between these modes has changed over time (see section 3). There is an extensive literature on mode effects, which shows that these may be ignorable for factual questions, but can be substantial in other domains (Couper 2011). For example, people often report worse health in online surveys than face-to-face ones (Tipping et al. 2010, Christensen et al. 2014, Klein et al. 2020, Braekman et al. 2020) – probably because of entangled mode and non-response effects (Couper 2011, Christensen et al. 2014). Differences between phone and in-person surveys are less likely because an interviewer is present in both (Couper 2011), compared to online or self-completion paper surveys. Nevertheless, respondents (particularly less-educated respondents) may make more shortcuts when responding to telephone surveys, which are also more subject to social desirability biases, both of which may lead to some differences in responses (Holbrook et al. 2003, Jäckle et al. 2010).

The impacts of proxies are even more complex. In order to collect as much data as possible, the LFS allows for “proxy responses” – responses by one individual on behalf of another. This arises because the LFS samples households rather than individuals, attempting to interview all individuals within a household. However, not all individuals in the household might be available simultaneously, and some may be unable or unwilling to respond. Proxy interviews are therefore common, which can be given by the parent of a child or young person, a carer on behalf of an elderly or infirm person, an adult on behalf of their partner or spouse, or a person of the same household on behalf of a non-English speaking relative (LFS user guide volume 1, section 5.5).

Conceptually, there are two main ways in which proxy responses may influence estimates of key economic indicators such as employment, unemployment and inactivity, as well as related measures such as disability (Thomsen and Villund 2011). On the one hand, proxies may improve the accuracy of economic indicators by ensuring that hard-to-reach groups are adequately represented in the data. Proxy responses for even subjective measures like ill-health have moderately strong validity (Hernández et al. 2023), and e.g. for a longitudinal study of older people, greater use of proxies can ensure that those with cognitive impairments are better-represented in the survey, reducing attrition bias (Weir et al. 2011)

Alternatively, proxies may harm the accuracy of economic indicators because the quality of responses is lower than self-reports – people generally know less information about other people than they do about themselves. It is widely accepted in studies of labour force surveys that "proxy interviews slightly underestimate employment rates" (Gauckler and Körner 2012:6). But proxy effects will be even stronger for more detailed, difficult-to-observe or subjective information. In a study of proxy responses in UK LFS telephone interviews, Dawe and Knight (1997) found slight error in proxy responses for economic activity status (7%), but greater levels of error for highest qualifications (37%), exact usual hours of work (62%) and income (34% error, with a correct response regarded as ±10% accuracy). There is also evidence that proxy reporting of disability can be quite inaccurate (Agrawal 2015), particularly for non-sensory limitations (Lee et al. 2007) such as mental health (Reimer et al. 2024).[3]

The effect of including proxy interviews in surveys is therefore complex – it depends on the balance of these mechanisms, which will vary according to how easy or difficult it is to reach different groups, and according to the type of question that is being asked. It also depends on the extent to which the response errors are random conditional on weighting variables (and can therefore be tackled through reweighting) or missing not at random (in which case reweighting cannot eliminate biases). Finally, it depends on the relationship between the proxy respondent and the person in question: spouses provide more accurate proxy responses than other household members (Lee et al. 2004). Similarly, Dawe and Knight (1997) find lower accuracy for parents describing the economic activity of their children compared to spouses describing their partners, albeit using a small sample.

The role of proxy responses can therefore not be determined *a priori.* In a Norwegian setting looking at the overall employment rate at one point in time, all of these effects combine such that it is better to include proxy interviews than to exclude them (Thomsen and Villund 2011). But in other settings, proxy responses may distort key economic data (e.g. within low-income countries; see Dervisevic and Goldstein 2023, Bardasi et al. 2011). There has been some suggestion that rises in mental illness in the LFS are greater in personal vs. proxy responses, but this does not discuss the changing extent of proxy responses over time (Blanchflower et al. 2024). To understand how these issues play out for UK trends in long-term sickness in the LFS, we need to understand the LFS methods in more detail, which is the focus of the next section.

3. LFS methods

The LFS is the largest regular social survey in the UK, and underpins the official statistics on employment, unemployment and inactivity published by the ONS. It has a long and (mostly) consistent time series since at least the 1990s – the LFS ran every other year from 1973 to 1983, then annually until 1991, and quarterly (in much the same form as today) from 1992.[4] The current LFS is available for rolling three-month periods, though we focus on calendar

[3] In interpreting these studies, we must bear in mind that even when the same person gives two responses about the same time period on different occasions, their responses may vary (Lee et al. 2007, Lemaitre 1988).
[4] See LFS User Guide Volume 1, section 1, for more details on the history of the LFS.

quarters in this paper. The data are available with only a short lag, which means it can provide up-to-date information, and has thus been influential in a range of policy debates.

The structure of the LFS is complex. Like other EU labour force surveys, the UK LFS attempts to follow people longitudinally, allowing an analysis of transitions (as well as providing a larger sample at lower cost). Sampled households are surveyed every three months for five “waves”, contributing to (up to) five consecutive quarters of data.[5] Respondents can (and often do) drop out after one or more waves, leading to attrition in the response rates.

The sample unit is the household, and all members of sampled households are surveyed. Households are mostly sampled from the Post Office’s Postcode Address File, with an attempt to remove business addresses. Additional samples are taken of households north of the Caledonian Canal in Scotland, households in Northern Ireland, and NHS accommodation. The target population is the resident population of the UK, and the data are weighted to be representative of this population. People who are usually resident of a sampled household but not currently living there, such as students living in halls of residence during term-time, are part of the target population and so included in the sampled household. The weighting is complex, using a five-stage process, accounting mostly for age, sex, and geographic distribution (see Appendix 2).

Fieldwork is usually carried out by both face-to-face and telephone interviews. Typically, households would be approached face-to-face in wave 1, and by telephone in subsequent waves. Some exceptions are that households in the far north of Scotland (north of the Caledonian Canal, ‘NoCC’) are always approached by telephone, and some interviews at later waves are also collected face-to-face where respondents request it. Prior to 2011, all wave 1 interviews were face-to-face apart from NoCC. Between 2011 and 2017, ONS used telephone interviewing for some wave 1 interviews where a telephone number could be matched to the sampled address.[6] That stopped from 2018 onwards, except in Northern Ireland and NoCC. However, the survey mode changed during the coronavirus pandemic, with all interviews (including wave 1) necessarily changing to telephone interviews, starting on 17 March 2020. In October 2023 face-to-face interviews were reinstated, but now for the initial *two* waves of the LFS, rather than just the first wave, and except for NoCC and in Northern Ireland.[7]

The LFS uses so-called “dependent interviewing” – that is, information from previous waves is available to interviewers at subsequent waves. This means that interviewers can check responses against previous responses to improve validity, and in the case of non-response (full or partial), previous responses are carried forward (for up to one wave only). Some “core” questions are not brought forward in this way, and must be asked without reference to previous responses. The “core” questions include many relating to work, but none of those we use to define long-term health conditions (see below). Therefore, questions relating to long-term health conditions may not be asked afresh in every wave, and so responses may be partly ‘sticky’, with subsequent responses influenced by past responses.

[5] See LFS User Guide, volume 1, section 3.2 for more details of the sample design and wave pattern of the sample.
[6] For Northern Ireland, the LFS is conducted by NISRA, so has followed different practices at times. The microdata suggest that all interviews at all waves in Northern Ireland were face-to-face until 2014 Q4.
[7] The variable *TYPINT* (type of interview) in the LFS microdata continues to show both face-to-face and telephone responses for periods since April 2020, but this is not reliable. In the empirical analysis we overwrite this variable for April-June 2020 to Jul-Sept 2023 as all telephone interviews.

Proxy responses

Proxy responses – that is, responses by a different person on behalf of the surveyed individual – are allowed on the LFS. The LFS User Guide Volume 1 suggests that proxy responses are "usually from another related adult who is a member of the same household" (p.38). However, it also lists a range of other example types of proxy responder:

i. a person, of the same household, may translate for a non-English speaking relative;
ii. a carer, of the elderly or infirm, although not related, may answer for someone in their care if it can be established that they know the respondent well enough;
iii. anyone can respond by proxy with the personal permission of the head of household or spouse.

Proxy responses are accepted for both face-to-face and telephone interviews, and have been accepted since the creation of the LFS. Since the household unit includes people temporarily living away, such as students living in halls of residence during term-time, proxy responses are also collected for people not physically present at the time of the interview. In section 4.1 below, we provide further results about changes over time in the use of proxy responses in the LFS.

Response rates

It has been widely observed that the LFS response rate has declined (Francis-Devine 2023, Corlett 2024). Figure 1 shows the response rates for wave 1 and waves 2-5 between 1993 and 2024. At the start of the quarterly LFS, response rates were above 80% at wave 1, and above 75% for waves 2-5 on average, for a total (all waves) response rate of just under 80%.[8] Response rates fell gradually and near-continuously for all waves over time, reaching about 50% for the total (all-waves) response rate in 2011-12, and about 40% in 2019. Throughout this time, the response rate at wave 1 was notably higher than at later waves.[9]

Response rates fell sharply during the coronavirus pandemic, likely partly associated with the forced shift to telephone-only interviewing, to a low of 12.7% for the total (all waves) response rate in July-Sept 2023. This led the ONS to temporarily suspend publication of labour market statistics, and to take steps to improve response rates – including the reintroduction of face-to-face interviews from October 2023 (ONS, 2023b) – after which the response rate has improved, but only to 23.9% by Oct-Dec 2025. The restoration of face-to-face interviews for LFS wave 1 and the start of face-to-face interviews for wave 2 in late 2023 did increase the response rates, but the wave 1 response rate is still noticeably below its pre-pandemic level. It is unclear why this is the case: it can be seen across multiple surveys, but a recent ONS review has also highlighted budget cuts leading to particular quality issues in the LFS (ONS 2024b). Not only do low response rates reduce the achieved sample from the original sample size, but they may increase the risk of non-response bias, although the relationship between response rates and response bias is complex and context-dependent (Groves and Peytcheva 2008).

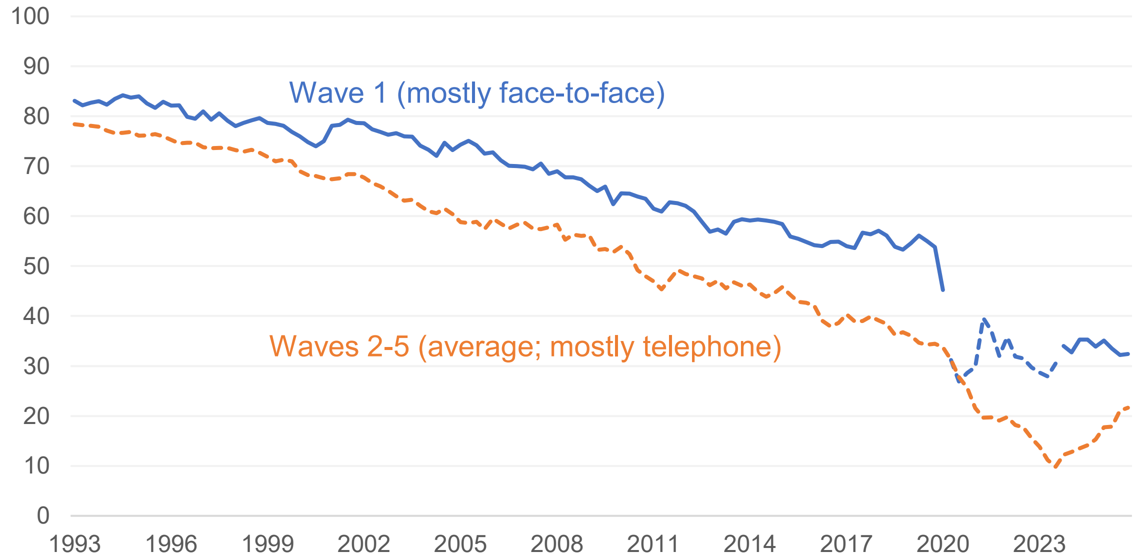
Figure 1 illustrates a further point which is less commonly noted – the difference (gap) in response rate between wave 1 (which is mostly face-to-face) and waves 2-5 (which are

[8] All response rates quoted in this section are "of eligible households" which includes most of the originally sampled addresses, and refusal in an earlier wave still counts as non-response in a later wave. As such, response rates for e.g. wave 5 are not only a fraction of responding households at wave 4.

[9] Response rates for waves 2-5 separately are only available from 1997 onwards, shown in Appendix 1. Response rates drop successively from wave 2 to wave 5, i.e. it is lower in wave 3 than wave 2, and so forth, but all are relatively similar (within 5-10pp) and all much lower than the wave 1 response rate. All waves show a similar declining pattern over time.

mostly by telephone) has widened over time. The percentage point difference between wave 1 and waves 2-5 was roughly 4-8pp from 1993-2001, rising to 10-16pp over 2002-2017, 17-21pp over 2018-2019, and 19-22pp over 2023-2024 (since the re-instatement of face-to-face interviews).[10] The *relative* difference is now much greater, such that the response rates at wave 1 are now around 2-2½ times that of waves 2-5 (compared to only about 10% higher in the 1990s, 20-30% higher in the 2000s, and 60% higher in 2019). This partly reflects a general decrease in telephone survey response rates observed internationally (Olson et al. 2021).

Figure 1 – Response rates to the UK Labour Force Survey (LFS), 1993-2025, by wave



Source: ONS, authors' calculations.
Notes: Compiled from multiple vintages of the LFS quality and monitoring report, and Barnes et al. (2008). Wave 1 is mostly face-to-face, and waves 2-5 are mostly by telephone, except between Apr-June 2020 and Jul-Sep 2021 when all waves were only via telephone (wave 1 is shown as a dashed line for this period), and from late-2023 when most wave 2 cases are also face-to-face. Data relate to calendar quarters since Jan-Mar 2006, prior to which the periods are Mar-May, Jun-Aug, Sep-Nov, Dec-Feb, due to data availability. Waves 2-5 are an appropriately weighted average until Apr-June 2008, and a simple average of the four waves thereafter. See Appendix 1 for response rates for each wave individually since 1997.

Measures used in this paper

This paper first explores trends in personal and proxy responding, before examining the impact of these on measures of long-term sickness, other measures of illness/disability, and total economic inactivity.

Personal responses are responses by an individual about themselves, while proxy responses are responses by an individual about another person. A third response type is possible: feed-forward imputation ("data brought forward") occurs when there in non-response in a given wave, but in the previous wave there was a valid response. Previous responses are 'fed forward' on only one occasion (one wave). The nature of response is identified by the LFS variable *IOUTCOME*. We report rates of personal and proxy response by age group, economic status and health status. We do this excluding the "data brought

[10] There is a period between April 2020 and March 2021 where the wave 1 telephone interview response rates were similar to that of other waves. From April 2021, a change was made to wave 1 telephone interviews so that interviewers physically visited the addresses of sample members where no telephone number was available, to obtain their telephone number and schedule a telephone appointment (termed 'Knock to Nudge') – the impact of this on response rates can be clearly seen in Figure 1.

forward" cases, such that the proxy response shares are of only genuine responses in a given quarter.

We also consider the type of proxy responder, which is identified by the LFS variable *PRXREL*. This takes two values, conditional on being a proxy response: "spouse/partner proxy" and "other proxy". The "other proxy" could include parents, carers, translators, siblings, children, or other nominated proxies.

We measure long-term sickness in this paper in a number of ways. The most widely used measure is people who are economically inactive (not employed, and not seeking or available to start a job) and report long-term sickness or disability as the main reason for their inactivity. This measure is reported by ONS in monthly LFS publication tables. It is identified by questions on what the main reason was for not looking for work in the last four weeks (*NOLWM*), and the main reason for not being available to start work (*YSTART*). These are combined in the derived variable *INECAC05* (*INECACR* before 2005).

An alternative and slightly broader measure is people who say that long-term sickness is a reason for inactivity, but not necessarily the main reason. This is identified using the (potentially multiple) reasons for not looking for work (*NOLOWA*). A subset of these will report that long-term sickness is the main reason for inactivity (as above).

We complement this with a broader measure of illness/disability, namely people who state that they have a long-term health condition (a health condition lasting, or expected to last, a year or more) and that it limits the 'kind' and/or 'amount' of paid work that they can do. The condition that the health condition is "work-limiting" in some way is relevant for study of the labour market. Both the employed and economically inactive can report work-limiting health conditions. The presence of a long-term health condition (of any kind) is identified by LFS variable *LNGLST* (*LNGLIM* before 2013), and whether it is work-limiting is identified by *LIMITK* for the kind of paid work and *LIMITA* for the amount of paid work.

Finally, respondents who say they have a long-term health condition can report one or more specific health conditions. The main type of long-term health condition is identified by *HEALTH20* (*HEALTH* before 2020), and the number of long-term health conditions is identified by adding the number of responses to the variable *HEAL20* (*HEAL* before 2020).

Analytical sample and weighting

Throughout we focus on people aged 16 to 64, which is the primary 'working-age' definition used in the LFS and associated statistics. We are especially interested in trends in long-term sickness and economic inactivity amongst the working-age population, as opposed to older people and health conditions *per se*. Some routing and derived variables on the LFS apply only to people of working age, such that this restriction improves comparability. However, the state pension age has risen over this period, so that by focussing on 16-64 year olds we exclude working-aged people aged 65+ (which applies from Mar 2019), and include some women over the state pension age (aged 60-64 before Nov 2018).

We use the weights supplied with the LFS microdata, notably the 2024 re-weighting (*PWT24*) which is available from Jan-Mar 2019 onwards, unless otherwise specified. Section 5 compares trends in long-term sickness and inactivity for different cuts of the LFS data. In all cases where we include only a subset of the data (e.g. only personal responses, or only wave 1 responses) we reweight the remaining data to match population totals, given by the sum of the weights of the full dataset. Specifically, we define age-sex-region-quarter cells, and proportionately re-scale the person weights of retained observations to match the sum of the weights of the cell in the full dataset. The full weighting procedure for the LFS is complex and not easily replicable, so we use an approach that is simpler but similar in spirit. See Appendix 2 for more details.

4. Analysing proxy responses on the LFS

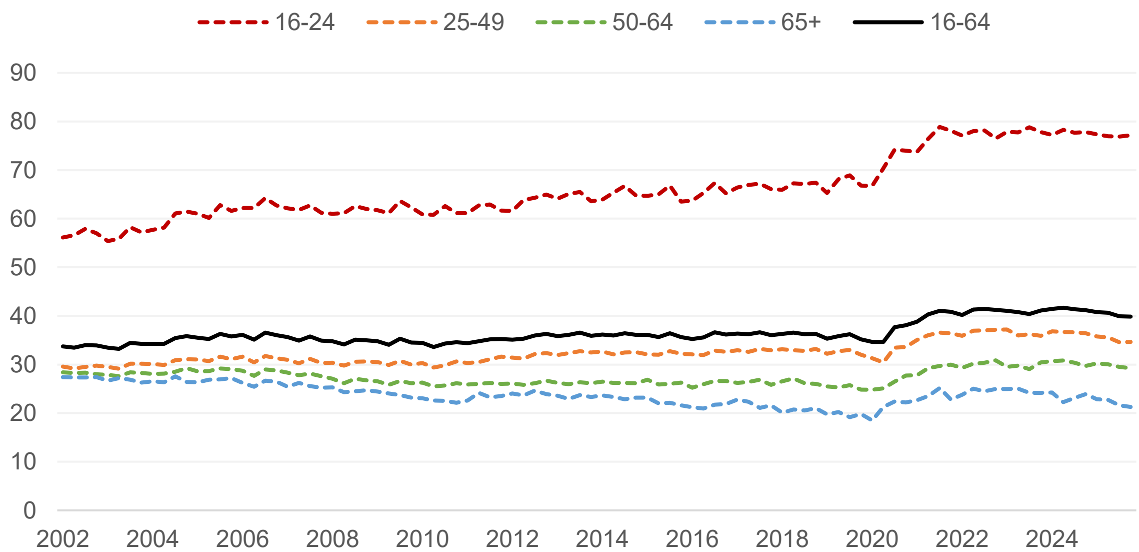
This section first documents the prevalence of proxy responses on the LFS, and how this has changed over time. We then explore how the rate of proxy responses varies across various individual characteristics.

4.1. Levels and patterns of proxy responses

Figure 2 shows the proportion of (weighted) proxy responses in individual responses in the LFS over time. Imputed cases (data brought forward) are excluded here, so responses are classified only as personal or proxy responses. For people aged 16 to 64, proxy responses account for around 40% of LFS data between 2021 and 2025, up from about 35% before the coronavirus pandemic – a rate that was fairly stable between 2002 and 2019.

There are large differences in the prevalence of proxy responses across age groups. The prevalence of proxies is highest amongst young people (and the very old, see Figure 3). Proxy responses account for nearly 80% of responses for people ages 16-24 since the pandemic, up from about two-thirds immediately before the pandemic. There has been a gradual upward drift in the proxy response rate for 16-24 year olds prior to the pandemic, likely associated with increasing participation rates in higher education (such that it was more often the case of young people living away from home in halls of residence, see section 2). By contrast, people aged 25-49 had proxy response rates a little below the 16-64 average, at about 35% post-pandemic and 32% prior. People aged 50-64 have proxy response rates around 30%, and people aged 65 and over (who we do not focus on in this paper) are lower still and with a slight downward trend in proxy response rates prior to the pandemic.

Figure 2 – Proportion of proxy responses (%) in the UK LFS, 2002 Q1 to 2025 Q4, by age group



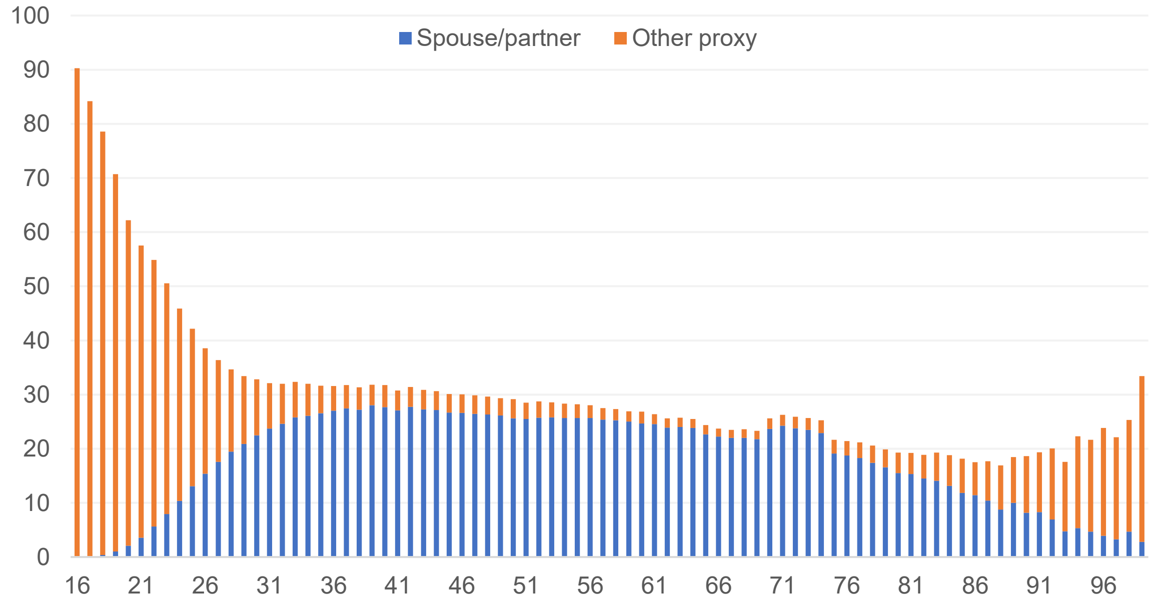
Source: LFS, authors' calculations.
Notes: Calendar quarters from Q1 (Jan-Mar) 2002 to Q4 (Oct-Dec) 2025. The denominator excludes data brought forward, so this is the proportion of proxy responses amongst 'genuine' (in-wave) personal and proxy responses only. Uses weighted data; trends in unweighted data are similar, if not more elevated post-pandemic, and are shown in Appendix 4.

The increase in proxy response rates during the pandemic occurs for all age groups. We suspect that telephone interviewing 1) increases the chances of reaching someone when others in the household are not available; 2) reduces the chances of multiple people in the household responding to the survey (i.e. sequentially being interviewed). The increase in proxy response rates in Figure 2 does not occur sharply in 2020 Q2 at the onset of the pandemic and shift to telephone-only interviewing, and instead the increase occurs over several quarters (levelling off from around mid-2021). The staggered impact on proxy responses probably reflects the fact that face-to-face interviews in wave 1 are likely to lead to lower proxy responses at *later* telephone waves, and Apr-Jun 2021 is the first time the five-quarter LFS includes no respondents who were initially interviewed face-to-face.

Figure 3 shows the proportion of proxy responses in individual responses in the LFS by individual year of age (16-99) and by type of proxy, using data pooled from 2002 to 2025. The only delineation of type of proxy responder in the LFS microdata is between “spouse/partner proxy” and “other proxy”, which are shown in Figure 3. Note that as this uses data pooled over 2002-2025, it largely reflects pre-pandemic data, but the patterns have not changed much post-pandemic.

Figure 3 confirms that young people have very high proxy response rates, which decrease sharply with age, such that the 16-24 group in Figure 2 hides considerable variation. For young people, the vast majority of proxy responses come from “other” proxies, which we assume are usually their parents or guardians. “Spouse/partner” proxies become more prevalent than “other” proxies from age 28 onwards, and account for the majority of proxy responses until age 90, when “other” proxies again become predominant. At very old ages, these “other” proxies are probably often carers or children.

Figure 3 – Proportion of proxy responses (%) in the UK LFS, by type of proxy, by individual year of age, 2002-2025 pooled



Source: LFS, authors’ calculations.
Notes: Based on pooled weighted data from Q1 2002 to Q4 2025. No information on type of proxy responder in the LFS microdata for 2020 Q4, so this quarter is excluded. The ‘empty space’ in the Figure corresponds to personal responses. The denominator excludes data brought forward, so this is the proportion of proxy responses amongst ‘genuine’ (in-wave) personal and proxy responses only.

Clearly proxy responses represent a large (perhaps surprisingly large) portion of LFS data, especially for young people. This does not seem to be a UK-specific phenomenon – for example, in Norway, proxy responses in their LFS were 15% pre-Covid, including over 60% of 15–19-year-olds (Li, 2018). Still, most of what we think we know about young people in the LFS is what their parents know.

Personal characteristics

Table 1 shows the prevalence of proxy responses by various personal characteristics and survey details, for different time periods. There is considerable persistent variation in proxy response rates across various personal characteristics and lots of nuance.

Regarding **sex**, proxy responses rates are much higher for men than women. That holds across all age groups, except for the over 65s where the rates are fairly even. This may relate to employment status (discussed below), with men typically having higher employment rates than women, or may relate to differences in attitudes towards surveys.

Regarding **employment status**, people who are employed had higher proxy response rates than people who are economic inactive before the pandemic, though that relationship seems to have flipped since then. The unemployed had the highest proxy response rates amongst employment statuses. Amongst the employed, those working full-time have higher proxy response rates than those working part-time. These patterns may reflect the availability at home to respond to the survey, with people working (especially full-time) likely to be less available at home than people who are not working.

Regarding **inactivity**, proxy response rates are relatively low (i.e. personal response rates are relatively high) across most main reasons for inactivity. Retired, long-term sick, temporarily sick, and looking after family/home are most likely to give personal responses – again, likely because these types of people are more likely to be contactable at home, compared to those who are working. These associations may partly reflect age, but the pattern broadly holds within age groups too (shown in Appendix 4). For example, young people who are looking after family/home (likely parents of young children) are highly likely to give a personal response, unlike other young people. The obvious exception is people who are inactive due to being students, for which proxy response rates are very high. This relates to the breakdown by age in Figures 2 and 3, and much of this will be due to young people temporarily living away from home.

Turning to **health**, it is harder to interpret the cross-sectional association between proxy responses and health because there is a two-way relationship here – someone's health may be reported differently by a proxy respondent than the person would report themselves; but simultaneously, health may affect whether someone provides a personal or proxy response:

- One way of interpreting this is that those who have a long-term health condition have, on average, lower proxy response rates (higher personal response rates) – possibly because they are more likely to be inactive or unemployed, and therefore more easily contactable, or they might have different attitudes towards completing surveys (e.g. are more pro-social). On average, those reporting more health conditions (and therefore likely of worse overall health) are more likely to give a personal response. Proxy response rates are relatively low across most types of main health condition. The main exception is those with cognitive disabilities (including learning difficulties) for whom proxy response rates are higher, likely to be where people are judged to lack the capacity to give a personal response.

- The other way of interpreting this is that people are more likely to report a long-term health condition in a personal response than in a proxy response (a bias that the wider literature suggests may be strongest for mental health conditions). Less reporting of health conditions by proxy responders might be because they are not aware of the health condition of the person they are reporting about, or they experience different interviewer effects when reporting about someone else's health than individuals experience when reporting about their own health.

Table 1 – Proportion of proxy responses (%) in the UK LFS, by various personal characteristics and survey details, multiple time periods

	2002-2012	2013-2019	2020-2025	*Full period (2002-2025)*
16-64	34.9	36.1	40.0	*36.5*
16-24	61.0	65.9	76.4	*66.3*
25-49	30.6	32.6	35.5	*32.4*
50-64	27.4	26.1	29.2	*27.5*
65+	25.3	21.8	23.2	*23.7*
Male	40.7	40.0	42.8	*41.0*
Female	27.7	29.5	34.0	*29.8*
Employed	34.9	35.1	37.8	*35.7*
Full-time	36.4	37.1	40.0	*37.5*
Part-time	27.0	27.2	33.1	*28.6*
Unemployed	36.2	37.2	44.0	*38.5*
Inactive	32.0	33.3	39.2	*34.2*
Inactive, main reasons:				
Student	67.1	70.8	80.7	*71.6*
Looking after family/home	23.0	26.0	31.2	*25.9*
Temporarily sick	23.1	26.0	30.8	*25.9*
Long-term sick	27.1	27.4	29.9	*27.9*
Discouraged worker	25.6	30.9	39.9	*30.8*
Retired	24.1	20.8	25.1	*23.4*
Other	31.4	31.1	39.0	*33.2*
No health condition	36.8	38.1	43.0	*38.7*
Has health condition	29.2	27.8	31.2	*29.3*
Physical	26.6	24.8	26.9	*26.2*
Sensory	33.3	29.9	32.1	*32.0*
Internal	30.1	28.2	30.8	*29.7*
Mental	24.6	25.8	29.8	*26.2*
Cognitive	51.4	56.1	63.8	*55.8*
Progressive	28.6	27.0	30.4	*28.6*
Other	28.8	28.3	30.1	*29.0*
Number of health conditions:				
1	33.0	32.1	35.8	*33.4*
2	27.9	26.2	30.4	*28.0*
3	24.2	23.1	26.6	*24.5*
4	22.4	20.7	24.4	*22.4*
5	21.9	19.7	21.7	*21.2*
6+	21.3	19.2	20.1	*20.4*
Wave 1	35.5	36.1	40.2	*36.9*
Wave 2	34.0	34.3	37.7	*35.0*
Wave 3	33.8	34.3	37.6	*34.9*
Wave 4	33.6	34.3	37.5	*34.8*
Wave 5	33.3	33.9	36.7	*34.3*
Face-to-Face	35.8	38.0	40.1	*37.1*
Telephone	33.0	31.6	37.7	*33.8*

Source: LFS, authors' calculations.
Notes: Groupings of main health problem described in Appendix. Breakdown for face-to-face and telephone for 2020-2025 overwrites identifying variable (*TYPINT*) in the microdata due to issues, and assumes no face-to-face interviews between 2020 Q2 and 2023 Q3 inclusive, so reflects an average excluding this period.

Most importantly for debates about rising health-related inactivity, these patterns have changed slightly in recent years. The increase in proxy response rates since the pandemic (seen in Figure 2) has generally been less sharp amongst people who have a long-term health condition – by 3.4pp (from 27.8% to 31.2%) for those with a health condition, compared with 4.9pp (from 38.1% to 43.0%) for those without a health condition, widening the gap that previously existed (see Table 1). Put the other way, personal response rates for people with a health condition have fallen a little post-pandemic but remain higher (68.8% over 2020-2025) than personal response rates for those without a health condition (57.0%).

This pattern also holds across age groups (shown in Appendix 4). However, the sharpest increase in proxy response rates is amongst young people with mental health conditions (see Appendix 4) – for this group, proxy response rates are up from about 50% until 2014, to about two-thirds in recent years. This still leaves the proxy response rate of young people with depression lower than young people without health conditions (and indeed lower than young people with other health conditions) but is nonetheless a sharp increase.

Predicting proxy responses

To disentangle these patterns, we look at the adjusted association of each factor with proxy response after controlling for other factors. To do this, we use a logistic regression model where we regress a binary measure of proxy response (taking the value one if the response is a proxy response and zero for a personal response) on gender, age group, housing tenure, LFS wave (dummies for each wave 2-5 vs. wave 1), and whether this is a telephone (vs. face-to-face) interview. The results are shown in Table 2 below.

Across the 2002-2025 period as a whole, long-term health conditions were associated with a *lower* chance of proxy responses, after controlling for other factors. The table shows logistic regression coefficients (here -0.16 in Model 1), but if we turn this into real-world probabilities (via marginal effects), then this is equivalent to a 3.2pp reduction in the chances of a proxy interview (95% CI -3.4pp to -3.1pp). However, Model 3 shows that this pattern is different pre- vs. post-pandemic (a regression coefficient of -0.12 pre-pandemic, but with a further -0.15 post-pandemic). If we again turn these into real-world probabilities, this translates to a 2.4pp (95% CI -2.5pp to -2.3pp) association pre-pandemic, but a -5.7pp (-5.9pp to -5.4pp) association post-pandemic.

Other associations are similar to the unadjusted picture in the previous section: proxy responses are less common pre-pandemic, among older age groups and for women (and not shown in the previous section, proxy responses are also slightly less common for those interviewed by phone).

Table 2 – Association of proxy response with different variables, logistic regression models using 2002-2025 pooled data

	LTHC		Post-pandemic		Interaction	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Controls for calendar quarters	Y		N		N	
Post-pandemic			0.33	0.003	0.37	0.004
Long-term health condition (LTHC)	-0.16	0.003			-0.12	0.003
LTHC X Post-pandemic					-0.15	0.007
Controls for employment status	Y				Y	
Phone (vs face-to-face) interview	-0.20	0.003	-0.20	0.003	-0.19	0.003
Female	-0.50	0.002	-0.58	0.002	-0.50	0.002
Age group (vs. 16-19)						
20-24	-1.27	0.006	-1.26	0.006	-1.26	0.006
25-29	-2.00	0.007	-1.98	0.006	-1.99	0.007
30-34	-2.23	0.007	-2.22	0.006	-2.23	0.007
35-39	-2.28	0.007	-2.29	0.006	-2.28	0.007
40-44	-2.33	0.007	-2.34	0.006	-2.33	0.007
45-49	-2.42	0.007	-2.43	0.006	-2.42	0.007
50-54	-2.52	0.007	-2.54	0.006	-2.51	0.007
55-59	-2.60	0.007	-2.65	0.006	-2.59	0.007
60-64	-2.66	0.007	-2.78	0.006	-2.66	0.007
Other variables included						
LFS wave	Y		Y		Y	
Housing tenure	Y		Y		Y	
n	5,012,668		5,012,668		5,012,668	

Source: LFS, authors' calculations.
Notes: Data shows logit coefficients (not odds ratios or predicted probabilities; see text). Analysis based on pooled weighted data from Q1 2002 to Q4 2025. No information on type of proxy responder in the LFS microdata for 2020 Q4, so this quarter is excluded. The proxy response outcome variable excludes data brought forward, so the table shows predictors of proxy (vs. personal) responses only.

5. The impact of proxies and survey wave on trends in sickness and inactivity

Section 4 demonstrated that proxy responses account for a large part of the LFS data (especially for young people), have risen in importance since the coronavirus pandemic, and vary in prevalence by personal characteristics (including health status). This section explores the robustness of trends in economic inactivity and long-term sickness to the inclusion of proxy responses, and to the survey mode.

Inactivity due to long-term sickness

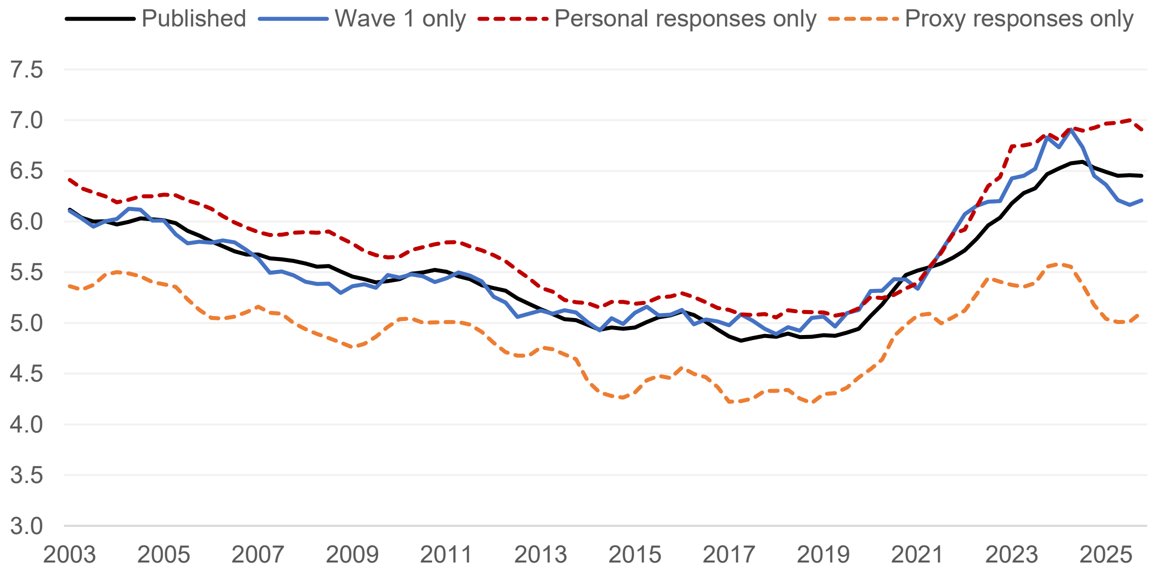
Figure 4 shows the proportion of the working-age population who are economically inactive, and say that the main reason is long-term sickness, from 2003 to 2025, for different cuts of the LFS data. The four lines are i) "Published" (the full dataset, including data brought forward), ii) "Wave 1 only", iii) "Personal responses only", and iv) "Proxy responses only" (the latter three series all reweighted to population totals as described in Appendix 2). We show four-quarter rolling averages to better observe trends, since the data are non-seasonally adjusted and a little noisy.

Looking first at the published LFS results (black line), we can see the rate of inactivity due to long-term sickness rising sharply from 2020, such that it is 1.5 percentage points [pp] higher (31%) in 2025 than in 2019 (comparing the four-quarter average to 2025 Q4 to the four-quarter average to 2019 Q4). When we compare these to our new series, we see:

- Looking at personal responses only (red line), the pattern over time is very similar and the increase is slightly larger, at 1.8pp (34%).
- By contrast, amongst proxy responses (orange line) the increase is slightly smaller, at 0.6pp (14%), partly due to a tailing off during 2025.
- If we just look just at the wave 1 data (blue line), which is mostly face-to-face before the pandemic and from end-2023 onwards, we again see a very similar pattern, but a slightly smaller increase of 1.1pp (21%), again with a tailing off during 2025.

Overall, it seems that the increase in long-term sickness may be smaller when accounting for changing response patterns and mode effects, best seen when focussing just on wave 1 responses. But the increase is still visible across all cuts of the LFS data we consider (e.g. just personal response) – the trend *per se* is not simply a methodological artefact. Aside from focusing on the trends, Figure 4 also highlights the differences in the levels of long-term sickness, in ways that are consistent with Table 1 that we discussed in section 4. Table 1 showed that personal responses are more prevalent amongst respondents with long-term health conditions (or put another way, personal responses are most likely to describe someone as having a long-term health condition). Thus, it follows that the rate of people with health problems (and inactive due to long-term sickness) would be higher amongst personal responses than amongst proxy responses, as in Figure 4. As discussed in section 4, it is not immediately obvious if this reflects selection effects (endogeneity between health status and response type) or differences in respondent behaviour (e.g. interviewer effects).

Figure 4 – Proportion of people aged 16-64 economically inactive with main reason of long-term sickness (%), four-quarter rolling averages, 2003 Q1 to 2025 Q4

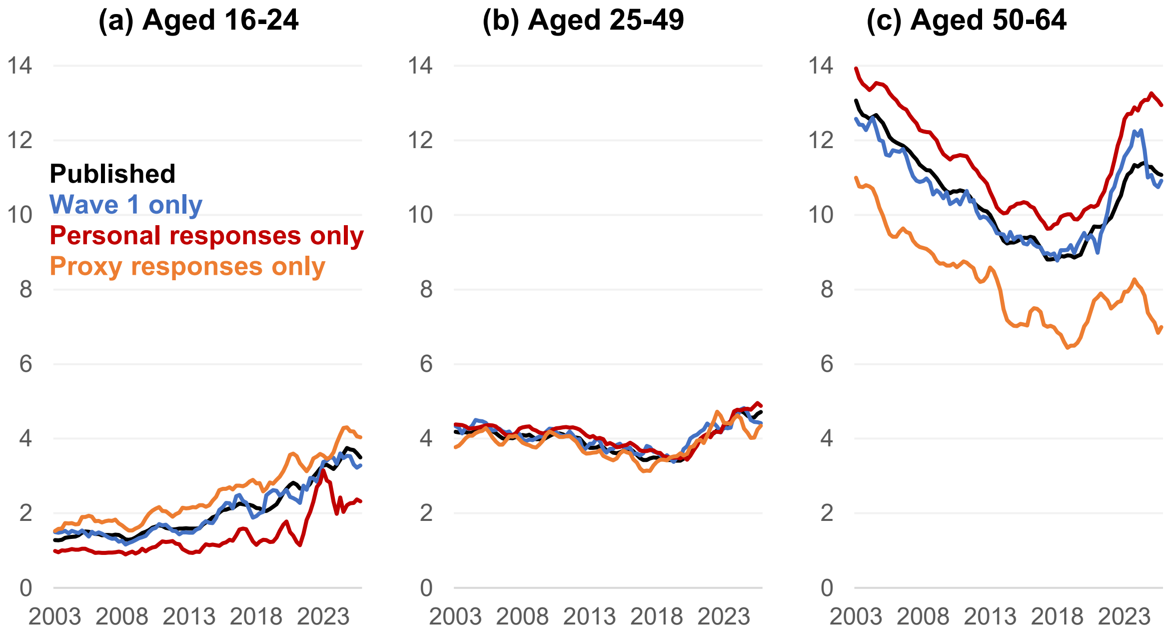


Source: LFS, authors' calculations.
Notes: Proportions of the population. "Published" is constructed from LFS microdata rather than from ONS publication tables, but uses the full dataset and is thus consistent with the published data. The other lines use a subset of the data and are re-weighted to match population totals – see text for details. Four-quarter trailing rolling averages of non-seasonally adjusted data.

Figure 5 shows the same pattern as Figure 4, but broken down by age group, with 16-24 year olds in panel (a), 25-49 year olds in panel (b), and 50-64 year olds in panel (c). All age groups, and all cuts of the data, show an increase in the rate of inactivity due to long-term sickness between 2019 and 2025. All cuts of the data show broadly consistent patterns for a given age group over 2003 to 2025 – for 50-64 year olds, a fall from 2003 and 2019 and then an increase; for 25-49 year olds, broadly flat from 2003 to 2019 and then an increase; and for 16-24 year olds, a gradual increase throughout.

Yet there are also some crucial differences by age here. For young people (aged 16-24), proxy responders are *more* likely to report inactivity due to long-term sickness, and this difference has been *rising* over time. Recall that proxy response rates are very high for 16-24 year olds, and will include a lot of people living away from home in halls of residence (though in that case you would expect them to be recorded as inactive mainly due to being students). For older working-age people (aged 50-64), proxy responders are *less* likely to report long-term sickness, and this has been *falling* over time (so that the gap increases) – indeed, there is a noticeable divergence for older people over the last year in long-term sickness reporting between personal vs. proxy responses. There are sizeable levels differences for the 50-64 age group, suggesting strong selection effects with respect to health status and response type. The middle age group (25-49) shows few differences between cuts of the data.

Figure 5 – Proportion of people economically inactive with main reason of long-term sickness (%), by age-group, four-quarter rolling averages, 2003 Q1 to 2025 Q4



Source: LFS, authors' calculations.
Notes: Proportions of the population of relevant age groups. "Published" is constructed from LFS microdata rather than from ONS publication tables, but uses the full dataset and is thus consistent with the published data. The other lines use a subset of the data and are re-weighted to match population totals – see text for details. Four-quarter trailing rolling averages of non-seasonally adjusted data.

There are various possible explanations for these differences, some of which are methodological (the achieved sample for 16-24 year olds is relatively small, so the trends are noisy), some of which are due to reporting (parents of younger people becoming more likely to attribute worklessness to sickness/disability than in the past), and some of which are substantive (that trends in long-term sickness are different for the types of people that give personal vs proxy responses, and this differs by age in ways that have changed over time). We recommend that future research interrogates this further, given that it has sizeable implications for understanding trends in long-term sickness.

Finally in this section, we look at how reporting of long-term sickness relates to proxy responses pre- vs. post-pandemic, net of other factors. Mirroring our analysis at the end of section 4, we look at the adjusted association of proxy responses with inactivity due to long-term sickness after controlling for other factors. To do this, we use a logistic regression model where we regress a binary variable for long-term sickness (taking the value one if the individual is inactive due to long-term sickness, and zero otherwise) on proxy response, gender, age group, housing tenure, LFS wave (dummies for each wave 2-5 vs. wave 1), and whether this is a telephone (vs. face-to-face) interview. The results are shown in Table 3.

Across the whole 2002-25 period, those providing proxy (rather than personal) responses were slightly more likely to report inactivity due to long-term sickness (a logit coefficient of 0.03). If we turn this into real-world probabilities using average marginal effects, then this is equivalent to proxy responders being 0.15 percentage points (95% CI 0.10pp to 0.20pp) to report long-term sickness.

However, this changes post-pandemic, as shown in Model 2 (where the interaction term is larger than the effect in the pre-pandemic period, at 0.09 vs. 0.01). In real-world terms, this is equivalent to essentially no difference between proxy and personal responders in the pre-pandemic period (proxy responders being only 0.03pp more likely to report long-term sickness [95% CI -0.02pp to 0.08pp]), but proxy responders being 0.50pp more likely to report long-term sickness post-pandemic (95% CI 0.36pp to 0.64pp).

Table 3 – Association of proxy responses with inactivity due to long-term sickness

	All years Coeff.	SE	**Pandemic effect** Coeff.	SE
Proxy (vs personal) response	0.03	0.005	0.01	0.005
Controls for calendar quarters	Y		N	
Post-pandemic			0.05	0.012
Proxy response X Post-pandemic			0.09	0.014
Other variables included				
LFS wave, phone vs. face-to-face	Y		Y	
Age, gender, housing tenure	Y		Y	
n	5,012,668		5,012,668	

Source: LFS, authors' calculations.
Notes: Data shows logit coefficients (not odds ratios or predicted probabilities; see text). Analysis based on pooled weighted data from Q1 2002 to Q4 2025. No information on type of proxy responder in the LFS microdata for 2020 Q4, so this quarter is excluded. The proxy response outcome variable excludes data brought forward, so the table shows proxy/personal) responses only.

Other measures of ill-health

We can also consider other measures of inactivity and long-term sickness, each of which captures a slightly different aspect of this phenomenon. The measure shown in Figures 4 and 5 – the proportion of people who give long-term sickness as their main reason for economic inactivity – is perhaps the strongest and narrowest definition. Other definitions, described in section 3, will capture other (often broader) notions of long-term sickness. Time series for a range of these are shown in Appendix 5, and summarised in Table 4.

All the measures of long-term sickness we consider broadly follow the same pattern: (i) an increase between 2019 and 2025; (ii) a slightly smaller increase (but an increase nonetheless in all cases) when we focus on the wave 1 responses only (which we expect to be more robust), except among 16-24 year olds for having a long-term health condition; and (iii) a larger increase when we limit to personal responses only, and smaller among proxy responses, except among 16-24 year olds (who have significant selection effects regarding response type). These findings are broadly consistent with the previous finding based on "inactivity due to long-term sickness": namely that the increase in long-term sickness and work-limiting disability persists across different cuts of the data, suggesting that the trend is not simply a methodological artefact.

That said, a notable pattern is that narrower (i.e. more restrictive) measures of long-term sickness show consistently smaller relative increases between 2019 and 2025. Using the full weighted dataset for the working-age population (16-64 year olds) as an example, Table 4 (first panel, first column) shows:

- 5.7pp increase in the proportion of people reporting that they have a long-term health condition;
- 3.8pp increase for those reporting they had a long-term health condition which limited the 'kind' of work they could do (3.4pp for the 'amount' of work);
- 1.6pp increase for people reporting long-term sickness as a reason (not necessary the main reason) for economic inactivity;
- 1.5pp increase for people reporting long-term sickness as the main reason for economic inactivity (as in Figure 4).

All other cuts of the data and age groups show the same relative pattern across increasingly narrower measures of long-term sickness or disability. This suggests that the increase in long-term sickness in the population is wide-spread, but not all of it is translating into observed labour market impacts (e.g. an increase in economic inactivity).

Table 4 also shows the change in the overall inactivity rate (irrespective of health status or reason for inactivity) for each age/sex group and cut of the data, in the final row of each panel. There appears to be more variation across the cuts of the data in respect of the inactivity rate than in respect of the sickness variables. However, this likely reflects selection effects and data noise to a large extent.

For people aged 16-24, the inactivity rate *increases* 1.2pp in the full dataset ("Published") but conversely *falls* 1.1pp when looking at personal responses only. In theory, this could reflect either reporting or selection effects. For reporting effects, it could be the case that parents are less likely to know than previously that their adult child (possibly living away at university) is working. Our view, though, is that it more likely to reflect selection effects – recall that proxy response rates are very high for 16-24 year olds, and will include a lot of people temporarily living away from home (e.g. in halls of residence). Between 2019 and 2025 there was an increase in the proportion of young people reporting they were inactive due to being students (many attending universities), which would overwhelmingly have proxy responses. Indeed, proxy response rates for this age group increased in recent years (Figure 2). Still, this does draw attention to how some headline findings are being driven by proxy responses.

For people aged 25-49, the full dataset shows a slight fall in inactivity rate (0.4pp), which is matched when looking at personal responses only (0.4pp), while proxy responses show a marked decrease (-1.6pp). In the case of proxy responses, this is driven by a sharp change in the second half of 2024 (notably for women in this age group) and should not be over-interpreted. Prior to 2019, this age group had seen a gradual and modest decline in inactivity rates, from 15-16% over 2002-05, 14-15% over 2006-13, 13-14% over 2014-17, and 12-13% over 2018-19. Since 2019 the inactivity rate has been essentially flat for this age group, so while there is no increase, there is a halt in the decline.

Table 4 – Change in proportion of people reporting long-term sickness and related measures between 2019 and 2025 (pp), various cuts of the data, by age group

	Published	Wave 1 only	Personal only	Proxy only
Age 16-64				
Have a long-term health problem	5.7	4.7	6.4	4.6
…which limits kind of work	3.8	2.9	4.2	2.6
…which limits amount of work	3.4	2.7	3.7	2.3
Long-term sickness as a reason for inactivity	1.6	1.1	1.9	0.7
Long-term sickness as main reason for inactivity	1.5	1.1	1.8	0.6
Inactivity rate	0.3	0.1	0.0	-0.4
Age 16-24				
Have a long-term health problem	5.1	5.4	5.0	5.5
…which limits kind of work	4.2	3.7	3.7	3.9
…which limits amount of work	3.8	3.4	3.6	3.3
Long-term sickness as a reason for inactivity	1.3	0.8	0.8	1.3
Long-term sickness as main reason for inactivity	1.1	0.8	0.8	1.1
Inactivity rate	1.2	2.2	-1.1	1.3
Age 25-49				
Have a long-term health problem	6.8	6.0	7.6	5.5
…which limits kind of work	3.9	3.4	4.4	3.1
…which limits amount of work	3.4	2.9	3.6	2.6
Long-term sickness as a reason for inactivity	1.4	1.0	1.5	0.7
Long-term sickness as main reason for inactivity	1.3	0.9	1.4	0.7
Inactivity rate	-0.4	-0.6	-0.4	-1.6
Age 50-64				
Have a long-term health problem	4.4	2.3	5.4	2.6
…which limits kind of work	3.3	1.6	4.3	1.0
…which limits amount of work	3.4	2.1	4.2	1.2
Long-term sickness as a reason for inactivity	2.3	1.6	3.1	0.5
Long-term sickness as main reason for inactivity	2.1	1.6	3.0	0.3
Inactivity rate	0.6	-0.2	1.0	0.3
Male (age 16-64)				
Have a long-term health problem	4.8	3.5	4.9	4.4
…which limits kind of work	3.0	2.2	3.1	2.2
…which limits amount of work	2.7	1.9	2.6	2.0
Long-term sickness as a reason for inactivity	1.5	1.2	1.7	0.8
Long-term sickness as main reason for inactivity	1.4	1.2	1.7	0.8
Inactivity rate	1.5	1.4	0.8	1.4
Female (age 16-64)				
Have a long-term health problem	6.6	5.7	7.8	4.8
…which limits kind of work	4.5	3.6	5.3	2.9
…which limits amount of work	4.1	3.4	4.8	2.5
Long-term sickness as a reason for inactivity	1.7	1.0	2.0	0.6
Long-term sickness as main reason for inactivity	1.6	0.9	1.9	0.5
Inactivity rate	-1.0	-1.3	-0.9	-2.3

Source: LFS, authors' calculations.
Notes: Units are percentage point change in the proportion of people in the population (within given age/sex category) reporting the given measure of long-term sickness or inactivity. "Published" uses the full LFS dataset, and so is consistent with published ONS statistical tables, though not all of these measures are actually published by ONS. The other columns use a subset of the data and are re-weighted to match population totals – see text for details. Time series charts for some of these breakdowns are in the Appendix.

However, this hides significant variation for men and women. Prior to the pandemic, men aged 25-49 had seen only a modest fall in inactivity rates from about 8% in the early 2000s to below 7% in 2019. In 2025, that figure had increased back above 8%. For women aged

25-49, the pre-pandemic decline was much sharper, from about 23% in the early 2000s to 18% in 2019. Since 2019 their inactivity rate has fallen a little further, to about 16% in 2025. These contrasting trends are broadly consistent across personal, proxy, and wave 1 responses.

For people aged 50-64, there is broad agreement amongst the cuts of the data. The pre-pandemic trend is downward, especially for women. The pandemic causes a sharp halt to that downward trend, and partial reversal. This is consistent broadly consistent across personal, proxy, and wave 1 responses.

Disentangling the endogeneity between health status, employment status and response type

A challenge in this analysis is the potential endogeneity between health status (having a long-term health condition or not), employment status (being economically inactive or not), and response type (personal or proxy). It is plausible that each of these factors influence the other, and so it is difficult to identify the effect of proxy responses on the reporting of health status independently.

One avenue to shed more light on this is through the use of longitudinal data. Due to the longitudinal structure of the LFS, with respondents interviewed for up to five consecutive quarters, it is possible to compare responses for some individuals in successive waves. We use the two-quarter (2Q) longitudinal LFS data, which includes all individuals who have responses in two consecutive waves.

Between consecutive waves, an individual could report: i) having a long-term health condition in both quarters, ii) not having a long-term health condition in both quarters, iii) not having a long-term condition in the first quarter but having one in the second, or iv) having a long-term health condition in the first quarter but not having one in the second. Our main approach will be to identify individuals the third case – that is, those who switch from reporting not to have a long-term health condition in one quarter, to having a long-term health condition in the next quarter – which we'll refer to as "acquiring a long-term health condition" for brevity.

Similarly, the type of response can vary between the two quarters, and for brevity we'll abbreviate personal responses by "P" and proxy responses by "X". Responses for an individual could be i) personal responses in both quarters (PP), ii) proxy responses in both quarters (XX), iii) personal response in the first quarter and proxy response in the second quarter (PX), or iv) proxy response in the first quarter and personal response in the second quarter (XP). Around 60% of the two-quarter data between 2012 and 2019 was PP, 30% XX, and 5% each for PX and XP. Since 2020, those rates have shifted given the overall shift towards proxy responses (Figure 2), to about 55% for PP, 40% for XX, and 3% each for PX and XP.

Table 5 summarises the rate of "acquiring a long-term health condition" between quarters, for different measures of long-term health conditions (as described in section 3) and for different response patterns. This uses two-quarter data pooled over 2012-2019 and 2020-2025, with the quarterly data being noisy.

We conclude the following. First, the rate of acquiring a long-term health condition has increased in the 2020-2025 period relative to the 2012-2019 period, across all measures and all response patterns. Thus, it does not appear that the increase in proxy responses is driving the increases in reported long-term health conditions (variously defined), since even amongst individuals giving personal responses in both quarters (PP), the rate of ‘acquiring’ a long-term health condition has increased.

Second, the rate of acquiring a long-term health condition tends to be highest for the Proxy-Personal (XP) response pattern in both time periods. To be clear, this is the case when no long-term health condition is reported by the proxy response in one wave, and then a long-term health condition is reported in the personal response in the subsequent wave. If we assume that personal responses are most reliable for a given individual, then the Personal-Personal (PP) response pattern should reveal the ‘true’ underlying rate of ‘acquiring’ a long-term health condition between quarters. For work-limiting long-term health conditions (second panel) that is about 2.4% of people per quarter on average in the 2012-2019 period. The difference between this rate, and the rate reported in the Proxy-Personal (XP) response pattern (3.1%), is an indicator of the bias induced by the proxy responder in the first quarter – in the case of work-limiting long-term health conditions in the 2012-2019 period, that bias is 0.7pp (3.1% minus 2.4%). The degree of bias increases in the 2020-2025 period to 1.8pp (5.2% minus 3.4%).

Third, we might still be concerned that acquiring a long-term health condition (variously defined) and switching response types are related. For instance, if someone develops a long-term health condition and leaves work as a result, they may be more available to give a personal response to the LFS in the second quarter. In that case, you would expect higher rates of acquiring long-term health conditions amongst the Proxy-Personal (XP) response pattern group, due to selection effects. The columns on the right side of Table 5 attempt to control for this by limiting it to respondents who are employed in both quarters, and the patterns still hold.

The only exception to this is long-term sickness as the main reason for inactivity (shown in the bottom panel of Table 5). While the rate of becoming economically inactive due to long-term sickness is higher for all response patterns in 2020-2025 compared with 2012-2019 (as for the broader measures of long-term sickness discussed above), the rate is not higher amongst the Proxy-Personal (XP) response pattern than the Personal-Personal (PP) response pattern. This suggests that any bias in proxy responses regarding long-term health conditions is primarily associated with having less work-limiting health conditions, i.e. not those that cause one to be economically inactive. Put another way, proxy responders might be more aware (and therefore more likely to accurately report) long-term health conditions where these are severe enough to cause economically inactivity, but less aware (and therefore less likely to accurately report) when they do not cause economic inactivity.

Two other points on longitudinal data are noteworthy. First, just as XP responses are associated with higher rates of ‘acquiring’ long-term health conditions (Table 5), they are also associated with a slightly higher rate of ‘losing’ long-term health conditions than Personal-Personal responses (see Appendix 6 for details). The differences are less stark than for acquiring long-term sickness, but still noticeable, and as before this also holds for those in employment in both periods. This indicates that proxy responders can sometimes report a long-term health condition that the individual in question later ‘rejects’. Since this effect is smaller than the effect on acquiring long-term health conditions, the net effect is still that proxy responders understate long-term health conditions.

Second, the rate of ‘losing’ long-term health conditions has also increased in the period 2020-2025 compared with 2012-2019 (see Appendix 6 for details). That is, there is increased churn rates in both directions. The increases are, on average, larger for the rates of acquiring long-term health conditions, such that the net effect is an increase in the inflow to the stock of people who have long-term health conditions. However, this could suggest that the collective interpretation of long-term health conditions has got 'fuzzier', leading to increased uncertainty about what to report and/or a greater degree of inconsistent reporting over time. This could suggest a need for stronger guidance for respondents when completing the survey.

Table 5 – Rate of acquiring a long-term health condition between successive quarters (%), by response pattern, different measures and time periods

	All persons			Employed in both quarters		
	2012-2019	2020-2025	Difference	2012-2019	2020-2025	Difference
Long-term health condition						
PP	4.0	4.8	0.8	4.1	5.0	0.9
PX	4.2	5.7	1.6	4.2	5.9	1.7
XP	7.1	8.7	1.6	7.2	9.5	2.3
XX	3.4	4.6	1.2	3.4	4.6	1.2
"Bias": XP-PP	*3.1*	*4.0*	*0.8*	*3.1*	*4.5*	*1.4*
Work-limiting long-term health condition						
PP	2.4	3.4	1.0	2.1	3.3	1.1
PX	2.2	3.5	1.3	1.9	3.2	1.3
XP	3.1	5.2	2.1	2.8	4.7	1.9
XX	1.8	2.8	1.0	1.6	2.4	0.8
"Bias": XP-PP	*0.7*	*1.8*	*1.1*	*0.7*	*1.4*	*0.8*
Economically inactive due to long-term sickness (main reason)						
PP	0.6	0.8	0.2			
PX	0.5	0.9	0.3			
XP	0.4	0.6	0.2			
XX	0.4	0.6	0.2			
"Bias": XP-PP	*-0.2*	*-0.2*	*0.0*			

Source: LFS, authors' calculations.

Notes: Uses pooled weighted data. Several quarters are missing as response type and/or health measure not available for one or both quarters in longitudinal LFS data: 2015Q1, all quarters or 2018, 2020Q3, 2020Q4, 2021Q3, 2022Q1. Response types: PP = Personal-Personal, PX = Personal-Proxy, etc. See Appendix for equivalent results for 'losing' a health condition.

6. Conclusion

This paper has provided evidence on the prevalence, distribution and impact of proxy responses on the UK LFS. Proxy responses account for a surprisingly high 40% of LFS data, up from about 35% before the pandemic. For young people (aged 16 to 24), proxy responses account for over 80% of the data, up from about two-thirds. Most of what we think we know about young people from the LFS is actually what their parents think they know.

Proxy response rates are higher (that is, personal response rates are lower) amongst people who are younger (and the very old), male, working full-time, economically inactive due to being a student, and/or do not have long-term health conditions. This is confirmed in conditional analysis as well as simple descriptives. There appears to be a complex interplay between health, economic status, and response type, which makes the pure effect of proxy responses on phenomena of interest difficult to disentangle.

We find that the trend of increasing rates of long-term sickness since the coronavirus pandemic are broadly robust to different cuts of the data, such as looking only at people giving personal responses or only data from wave 1. We also examine multiple measures of long-term sickness on the LFS – including measures that indicate more and less work-limiting health problems – which all show broadly the same trends. We therefore conclude that proxy responses and survey mode are not the principle causes of the increased rates of reported long-term sickness and long-limiting disability. Indeed, using longitudinal LFS data, we find some tentative evidence that proxy responders tend to under-report long-term health conditions. Given the increase in proxy responses since the pandemic, this may even suggest that the rise in long-term sickness is understated on the LFS. However, this finding with the longitudinal data does not extend to economic inactivity due to long-term sickness.

However, all of these findings still depend on the quality of the LFS more broadly. Other studies have compared trends in the LFS with trends from other sources, with mixed results. One recent study finds that trends in self-reported survey data on disability benefit receipt (from the Family Resources Survey and LFS) match the administrative data on claims for Personal Independence Payments fairly well, while other surveys do not (IFS, 2025). While we judge that trends in long-term sickness in the LFS are broadly robust to two aspects of LFS methodology, this does not validate the LFS in general. More systemic issues with the LFS could still undermine the results.

We conclude with some comments on economic measurement. First, we suggest that researchers and analysts using the LFS should be mindful of the role of proxy responses on their findings. We recommend considering trends in personal and proxy responses separately, as we have done in this paper. Similarly, focussing on wave 1 responses and/or splitting by survey mode (face-to-face and telephone) may be valuable. This may be especially important in the analysis of young people, for whom proxy response rates are very high. There are also substantial selection effects: young people temporarily living away from the family home (e.g. in halls of residence) will usually have a proxy response (presumably by their parents or guardians), while young people giving personal responses will tend to live in the family home. Thus, the LFS data on young people could be considered two sets of quite distinct data about two sets of distinct young people.

Second, our analysis does not lead to a recommendation regarding the use of proxy responses on the LFS. There are theoretical advantages and disadvantages of proxy responses in surveys, and we have seen both at play in our analysis. We therefore do not advocate either for their inclusion nor exclusion on the LFS. We do, however, advocate for more information on the extent and effect of proxy responses be made available. The last study of the effect of proxy responses on the LFS was Dawe and Knight (1997) which is nearly 30 years old, and response rates have fallen over 50 percentage points in that time (from roughly 75% in 1997 to around 20% in recent years). The ONS could conduct a study of the quality of proxy responses on the LFS today.

The ONS is also developing an online-first survey to replace the LFS (known as the TLFS) and should carefully consider the role of proxy responses in that survey. The effect of proxy responses may be different in an online mode compared with the face-to-face and telephone modes of the current LFS. Given the flexibility of responding in an online mode, it is possible that proxy response rates would be lower compared with the LFS for a given overall response rate – if so, that could lead to an improvement in data quality, all else equal. Any change in the number or type of proxy responders in the TLFS relative to the LFS might have implications for discontinuities between the two surveys, and could be accounted for in discontinuity, reconciliation and time series analysis. Finally, ONS may wish to consider differential survey guidance or routing for proxy responders as compared to personal responders. For instance, some questions may be more suitable for proxy responders than others (e.g. more objective questions, about which proxy responders would be expected to give more reliable response). The online mode might enable more sophisticated routing or data collection techniques that account for the likely impact of proxy responses.

References

Agrawal, G. (2015), Self-vis-à-vis-proxy reported morbidity prevalence among adults in India: a study based on the national sample survey. *International Journal of Human Rights in Healthcare,* 8, 1: 14-21.

Ayoubkhani, D., Zaccardi, F., Pouwels, K.B., Walker, S.A., Houston, D., Alwan, N.A., Martin, J., Khunti, K., Nafilyan, V. (2024). "Employment outcomes of people with Long Covid symptoms: community-based cohort study," European Journal of Public Health, 34(3), 489-496, https://doi.org/10.1093/eurpub/ckae034

Bardasi, E., Beegle, K., Dillon, A. & Serneels, P. (2011), Do Labor Statistics Depend on How and to Whom the Questions Are Asked? Results from a Survey Experiment in Tanzania. *The World Bank Economic Review,* 25, 3: 418–447.

Barnes, W., Bright, G. and Hewatt, C. (2008). "Making sense of Labour Force Survey response rates," *Economic & Labour Market Review, 12(2)*, 32-42.

Blanchflower, D.G., Bryson, A. and Bell, D.N.F. (2024) "The Declining Mental Health of the Young in the UK," NBER Working Paper 32879, https://doi.org/10.3386/w32879

Braekman, E., Charafeddine, R., Demarest, S., et al. (2020), Comparing web-based versus face-to-face and paper-and-pencil questionnaire data collected through two Belgian health surveys. *International Journal of Public Health,* 65, 1: 5-16.

Burn-Murdoch, J. (2022). "Chronic illness makes UK workforce the sickest in developed world". *Financial Times article.* Available: https://www.ft.com/content/c333a6d8-0a56-488c-aeb8-eeb1c05a34d2

Boys, J. (2022). "Can demography explain the missing older workers?" *CIPD Blogs.* Available: https://community.cipd.co.uk/cipd-blogs/b/cipd_voice_on/posts/can-demography-explain-the-missing-older-workers

Christensen, A. I., Ekholm, O., Glümer, C. & Juel, K. (2014), Effect of survey mode on response patterns: comparison of face-to-face and self-administered modes in health surveys. *The European Journal of Public Health,* 24, 2: 327-332.

Corlett, A. (2024), Get Britain's Stats Working: Exploring alternatives to Labour Force Survey estimates. London, Resolution Foundation.

Couper, M. P. (2011), The future of modes of data collection. *Public Opinion Quarterly,* 75, 5: 889-908.

Dawe, F. & Knight, I. (1997), A study of proxy response in the Labour Force Survey. *Survey Methodology Bulletin,* 40.

Dervisevic, E. & Goldstein, M. (2023), He said, she said: The impact of gender and marriage perceptions on self and proxy reporting of labor. *Journal of Development Economics,* 161: 103028.

Favilukis, J. and Li, G. (2023). "The Great Resignation was caused by the Covid-19 housing boom". *Working paper.* Available at SSRN: https://ssrn.com/abstract=4335860

Francis-Devine, B. (2023), Has labour market data become less reliable? , *House of Commons Library*.

Gauckler, B. & Körner, T. (2012), Measuring the employment status in the Labour Force Survey and the German Census 2011: insights from recent research at Destatis. *Methoden, Daten, Analysen (mda),* 5, 2: 181-205.

Groves, R. M. & Peytcheva, E. (2008), The Impact of Nonresponse Rates on Nonresponse Bias: A Meta-Analysis. *Public Opinion Quarterly,* 72, 2: 167-189.

Haskel, J. (2022). "Recent UK monetary policy in a changing economy". *Speech given at Bank of Israel, November 2022. Available*: https://www.bankofengland.co.uk/speech/2022/november/jonathan-haskel-seminar-at-bank-of-israel

Haskel, J. & Martin, J. (2022), Economic inactivity and the labour market experience of the long-term sick. London, Imperical College London. Available:

Health Foundation (2024), Towards a healthier workforce: Interim report of the Commission for Healthier Working Lives.

Hernández, J. D., Spir, M. A., Payares, K., et al. (2023), Assessment by proxy of the SF-36 and WHO-DAS 2.0. A systematic review. *J Rehabil Med,* 55: jrm4493.
Holbrook, A. L., Green, M. C. & Krosnick, J. A. (2003), Telephone versus Face-to-Face Interviewing of National Probability Samples with Long Questionnaires: Comparisons of Respondent Satisficing and Social Desirability Response Bias. *The Public Opinion Quarterly,* 67, 1: 79-125.
House of Lords Economic Affairs Committee (2022), Where have all the workers gone? , *2nd Report of Session 2022-23 - HL Paper 115*, London, The Stationery Office.
IFS (2022), " The number of new disability benefit claimants has doubled in a year IFS". Available: https://ifs.org.uk/publications/number-new-disability-benefit-claimants-has-doubled-year
IFS (2025), "The role of changing health in rising health-related benefit claims". Available: https://ifs.org.uk/publications/role-changing-health-rising-health-related-benefit-claims
Jäckle, A., Roberts, C. & Lynn, P. (2010), Assessing the Effect of Data Collection Mode on Measurement. *International Statistical Review / Revue Internationale de Statistique,* 78, 1: 3-20.
Klein, J. W., Tyler-parker, G. & Bastian, B. (2020), Measuring psychological distress among Australians using an online survey. *Australian Journal of Psychology,* 72, 3: 276-282.
Lee, S., Mathiowetz, N. A. & Tourangeau, R. (2004), Perceptions of disability: the effect of self-and proxy response. *Journal of Official Statistics,* 20, 4: 671.
Lee, S., Mathiowetz, N. A. & Tourangeau, R. (2007), Measuring Disability in Surveys: Consistency Over Time and Across Respondents. *Journal of Official Statistics,* 23, 2: 163.
Lemaitre, G. (1988), A look at response errors in the labour force survey. *Canadian Journal of Statistics,* 16, S1: 127-141.
Li, L. (2018), Proxy Interviews in the Norwegian Labour Force Survey. Analysis of self-respondent and proxy interviews, and their impact on estimates. Statistics Norway.
Murphy, L. (2024), "A U-Shaped Legacy: Taking stock of trends in economic inactivity in 2024". Available: https://www.resolutionfoundation.org/publications/a-u-shaped-legacy/
Murphy, L. and Thwaites, G. (2023). "Post-pandemic participation: Exploring labour force participation in the UK, from the Covid-19 pandemic to the decade ahead". *Resolution Foundation, February 2023.* Available: https://www.resolutionfoundation.org/app/uploads/2023/02/Post-pandemic-participation.pdf
OBR (2023), Fiscal risks and sustainability – July 2023. *CP 870*, London, Office for Budget Responsibility (OBR).
Olson, K., Smyth, J. D., Horwitz, R., et al. (2021), Transitions from telephone surveys to self-administered and mixed-mode surveys: AAPOR task force report. *Journal of Survey Statistics and Methodology,* 9, 3: 381-411.
ONS. (2022a). "Worker movements and economic inactivity in the UK: 2018 to 2022". *ONS website article.* Available: https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment/articles/workermovementsandinactivityintheuk/2018to2022
ONS. (2022b). "Reasons for workers aged over 50 years leaving employment since the start of the coronavirus pandemic: wave 2". *ONS website article.* Available: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/reasonsforworkersagedover50yearsleavingemploymentsincethestartofthecoronaviruspandemic/2022-03-14
ONS. (2023a). "Population changes and economic inactivity trends, UK: 2019 to 2026". ONS website article. Available: https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/economicinactivity/articles/populationchangesandeconomicinactivitytrendsuk2019to2026/2023-03-03

ONS (2023b), Labour Force Survey: planned improvements and its reintroduction. Office for National Statistics (ONS).

ONS (2024a), Labour Force Survey performance and quality monitoring report: July to September 2024. Office for National Statistics (ONS).

ONS (2024b), Transformed Labour Force Survey - A Lessons Learnt Review. Office for National Statistics (ONS).

Ray-Chaudhuri, S. & Waters, T. (2024), Recent trends in and the outlook for health-related benefit. London, Institute for Fiscal Studies.

Reimer, C., Ali-Thompson, S., Althawadi, R., O'Brien, N., Hickey, A. & Moran, C. N. (2024), Reliability of proxy reports on patient reported outcomes measures in stroke: An updated systematic review. *Journal of Stroke and Cerebrovascular Diseases,* 33, 6: 107700.

Reuschke, D. and Houston, D. (2023). "The impact of Long COVID on the UK workforce", Applied Economics Letters, 20(18), 2510-2514, https://doi.org/10.1080/13504851.2022.2098239

Thomsen, I. & Villund, O. (2011), Using Register Data to Evaluate the Effects of Proxy Interviews in the Norwegian Labour Force Survey. *Journal of Official Statistics,* 27, 1: 87–98.

Tinson, A., Major, A. and Finch, D. (2022), "Is poor health driving a rise in economic inactivity?" *Health Foundation, October 2022.* Available: https://www.health.org.uk/reports-and-analysis/analysis/is-poor-health-driving-a-rise-in-economic-inactivity

Tipping, S., Hope, S., Pickering, K., Erens, B., Roth, M. A. & Mindell, J. S. (2010), The effect of mode and context on survey results: Analysis of data from the Health Survey for England 2006 and the Boost Survey for London. *BMC Medical Research Methodology,* 10, 1: 84.

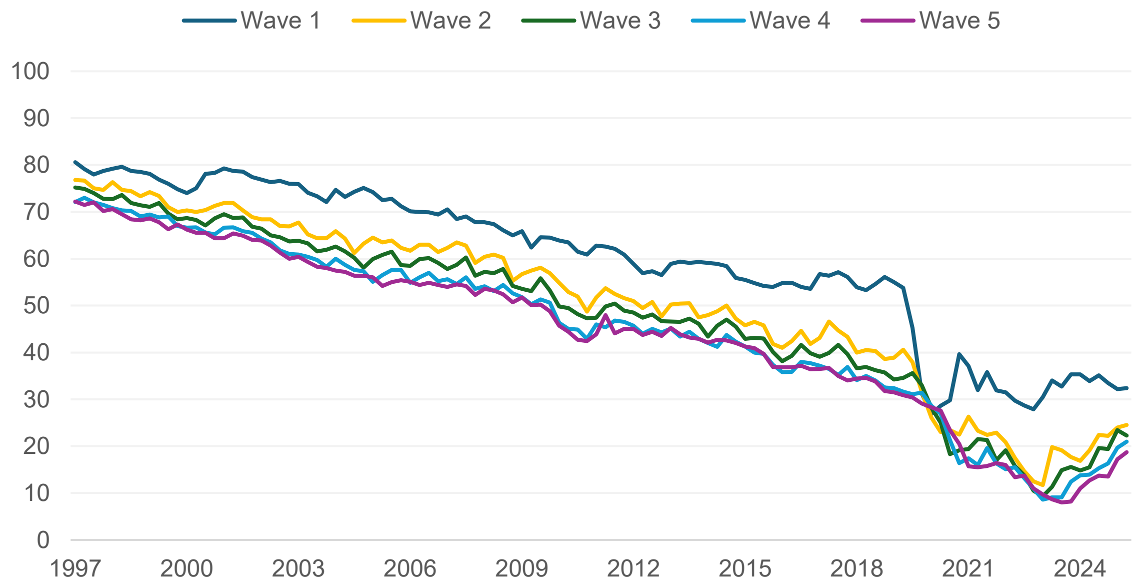
Weir, D., Faul, J. & Langa, K. (2011), Proxy interviews and bias in cognition measures due to non-response in longitudinal studies: a comparison of HRS and ELSA. *Longitudinal and Life Course Studies,* 2, 2: 170-184.

Appendices

Appendix 1: LFS response rates by wave

In the main text, Figure 1 shows the response rates in the LFS split between wave 1 and wave 2-5 combined. The figure below provides additional detail by separating waves 2-5.

Figure A1 – Response rates to the UK Labour Force Survey (LFS), 1997-2025, by wave



Source: ONS, authors' calculations.
Notes: Compiled from multiple vintages of the LFS quality and monitoring report, and Barnes et al. (2008). Data relate to calendar quarters since Jan-Mar 2006, prior to which the periods are Mar-May, Jun-Aug, Sep-Nov, Dec-Feb, due to data availability.

Appendix 2: Process for re-weighting subsets of the LFS data

The construction of weighs for the quarterly LFS is described in the LFS User Guide Volume 1, from which the following is summarised. The LFS uses "calibration weighting" whereby each individual in a group is assigned a weight, and the weights for individuals in a group sum to the known (or assumed) population total of that group. The LFS uses five calibration groups (partitions) defined variously by age, sex, region, local authority, and/or housing tenure. Each individual would receive five different calibration weights, one for each partition; but the weight is calibrated simultaneously across all five partitions using a specialist software to ensure all approaches achieve population totals (within a tolerance). The five partitions are:

1. Individual local authority districts (up to 433 local authorities, with some potentially being merged in the case of low counts where necessary)
2. Sex by age-groups for Great Britain and Northern Ireland (GB: 0-15, 16, 17, 18, 19, 20, 21, 22, 23, 24 and 25+; NI: 0-15, 16-17, 18- 20, 21- 22, 23- 24 and 25+)
3. Sex by age-group (0-15, 16-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75+) and ITL1 region (nine English regions, Scotland, Wales and Northern Ireland)
4. Sex by age-groups for Great Britain and Northern Ireland (0-4, 5-9, 10-15, 16-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75+)
5. Housing tenure based on 2021 census (Owned outright, mortgage or loan, and Rent)

This is a complex procedure which is not possible to replicate precisely. We use a simpler but similar weighting process to re-weight the data back to population totals when using subsets of the data – such as when using only Wave 1 responds, only personal responses, or only proxy responses.

For our re-weighting we construct population totals from the full dataset by sex, age-group, and ITL1 region. We use age-groups: 16-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80), broadly consistent with partition 4. The use of ITL1 regions covers the geographical splits in partitions 2, 3 and 4. The data counts for subsets of the LFS data (e.g. personal responses only) do not allow for the detailed age-groups used in partition 2, or the detail geographical breakdown in partition 1. We judge that our approach provides a sufficient approximation.

Appendix 3: Grouping of main health problems

The LFS collects “main health problem” (for respondents who have a long-lasting health problem) in the variable HEALTH20 (replacing HEALTH from 2020 onwards). This includes 18 categories (one added in HEALTH20 as compared to HEALTH). Many of these categories are too small (i.e. too infrequently reported) to be separately identified in our analysis. As such, we aggregate these 18 health problems into 7 groups, as detailed below. The LFS does provide an aggregation into five groups in that variation HEALTH20B (replacing HEALTH20), but we found this grouping to be analytically unhelpful, since some of these groups remain quite small and others quite diverse. Particular limitations with HEALTH20B included: small size of group 2; combining learning difficulties with depression and mental illness; the size and diversity of group 5. As such, we developed our own categorisation that seeks to better align types of health categories, provides an intermediate level of detail (seven groups rather than five), and better balance the size of the groups.

Table A1 – Classification of main health conditions into categories used in this paper

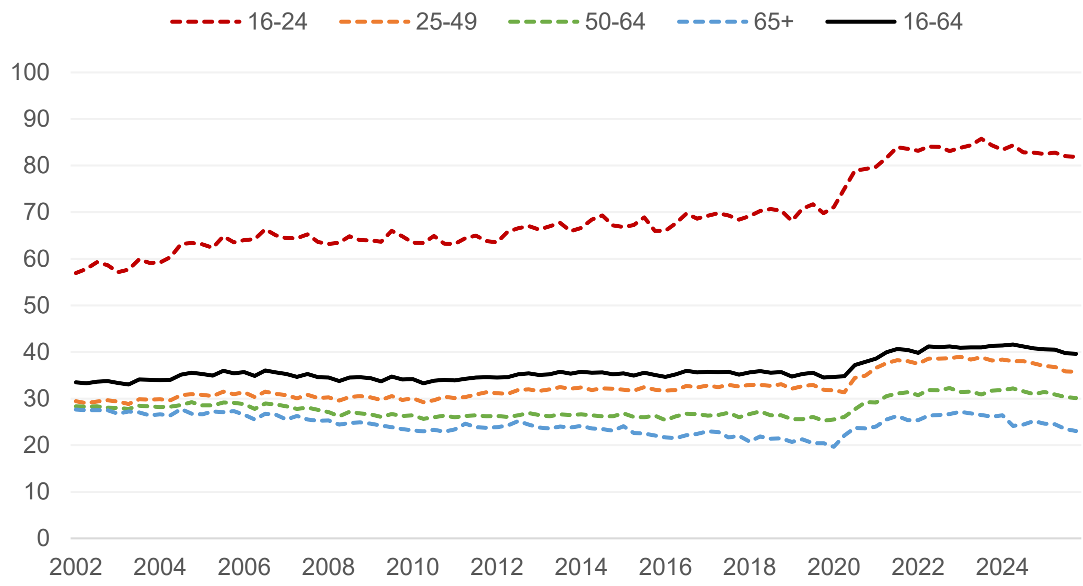
	Detailed categories (HEALTH20 and HEALTH)	**Categories used in this paper**	**Categories in HEALTH20B and HEALTHB**
1	Problems or disabilities (including arthritis or rheumatism) connected with arms or hands	Physical	1
2	Problems or disabilities (including arthritis or rheumatism) connected with legs or feet	Physical	1
3	Problems or disabilities (including arthritis or rheumatism) connected with back or neck	Physical	1
4	Difficulty in seeing (while wearing spectacles or contact lenses)	Sensory	2
5	Difficulty in hearing	Sensory	2
6	A speech impediment	Sensory	5
7	Severe disfigurement, skin conditions, allergies	Physical	5
8	Chest or breathing problems, asthma, bronchitis	Internal	3
9	Heart, blood pressure or blood circulation problems	Internal	3
10	Stomach, liver kidney or digestive problems	Internal	3
11	Diabetes	Internal	3
12	Depression, bad nerves or anxiety	Mental	4
13	Epilepsy	Cognitive	5
14	Severe or specific learning difficulties	Cognitive	4
15	Mental illness, or suffer from phobia, panics or other nervous disorders	Mental	4
16	Progressive illness not included elsewhere (e.g. cancer, multiple sclerosis, symptomatic HIV, Parkinson’s disease, muscular dystrophy)	Progressive	5
17	Other health problems or disabilities	Other	5
18	Autism (including Autism Spectrum Condition, Asperger syndrome)	Cognitive	5

Note: Autism (18) was added in HEALTH20 and HEALTH20B, and not separately identified previously.

Appendix 4: Additional detail on proxy response rates

In the main text, Figure 2 shows the proportion of proxy responses in weighted data. The corresponding figure using unweighted data is shown below.

Figure A2 – Proportion of proxy responses in unweighted data (%) in the UK LFS, 2002 Q1 to 2025 Q4, by age group



Source: LFS, authors' calculations.
Notes: Calendar quarters from Q1 (Jan-Mar) 2002 to Q4 (Oct-Dec) 2025. The denominator excludes data brought forward, so this is the proportion of proxy responses amongst 'genuine' (in-wave) personal and proxy responses only. Uses unweighted data; trends in weighted data are similar, shown in Figure 2 in the main text.

In the main text, Table 1 shows trends in proxy responses according to age, inactivity and health condition. It also adds, *"This pattern also holds across age groups (shown in the Appendix). However, the sharpest increase in proxy response rates is amongst young people with mental health conditions (see Appendix 4) – for this group, proxy response rates are up from about 50% until 2014, to about two-thirds in recent years. This still leaves the proxy response rate of young people with depression lower than young people without health conditions (and indeed lower than young people with other health conditions) but is nonetheless a sharp increase."* This is shown in the table below.

Table A2 – Proportion of proxy responses (%) in the UK LFS, by main reason for inactivity and type of long-term health problem by age group, multiple time periods

	2002-2012	2013-2019	2020-2025	*Full period (2002-2025)*
16-24				
Not inactive	58.8	62.6	72.2	*63.3*
Inactive, main reasons:				
Student	73.5	75.8	85.7	*77.2*
Looking after family/home	20.1	24.3	34.0	*24.8*
Temporarily sick	52.3	58.1	78.4	*60.5*
Long-term sick	69.1	77.3	82.1	*74.7*
Discouraged worker	67.1	75.5	79.7	*72.7*
Retired	-	-	-	-
Other	61.4	67.4	78.8	*67.5*
No long-term health condition	61.4	66.7	78.1	*67.1*
Main health problem:				

Physical	55.4	57.9	66.9	*59.0*
Sensory	63.9	68.5	76.2	*68.3*
Internal	57.9	61.0	69.3	*61.6*
Mental	47.9	53.6	65.2	*53.8*
Cognitive	73.9	81.8	87.3	*79.5*
Progressive	67.1	70.2	76.1	*70.2*
Other	59.6	68.8	71.4	*65.2*
25-49				
Not inactive	31.6	33.2	35.7	*33.1*
Inactive, main reasons:				
Student	26.0	29.7	35.2	*29.4*
Looking after family/home	22.4	26.8	32.3	*26.2*
Temporarily sick	20.2	24.5	28.1	*23.4*
Long-term sick	28.4	30.4	35.0	*30.6*
Discouraged worker	36.9	41.0	49.2	*41.2*
Retired	31.2	33.0	40.5	*34.1*
Other	28.5	31.9	39.6	*32.2*
No long-term health condition	31.6	34.2	38.1	*34.0*
Main health problem:				
Physical	26.8	26.8	29.1	*27.3*
Sensory	31.1	31.2	32.9	*31.6*
Internal	29.5	30.4	32.4	*30.4*
Mental	22.3	21.9	25.3	*22.9*
Cognitive	42.7	47.3	52.7	*46.5*
Progressive	25.3	25.4	31.4	*26.8*
Other	25.2	25.6	27.1	*25.8*
50-64				
Not inactive	29.6	28.1	30.9	*29.5*
Inactive, main reasons:				
Student	16.7	22.6	26.3	*20.8*
Looking after family/home	26.9	25.4	29.6	*27.2*
Temporarily sick	16.3	16.7	17.1	*16.6*
Long-term sick	22.3	19.7	20.2	*21.0*
Discouraged worker	14.7	20.3	24.5	*18.8*
Retired	23.4	21.1	28.6	*24.0*
Other	20.7	20.2	24.9	*21.6*
No long-term health condition	29.5	28.8	32.8	*30.1*
Main health problem:				
Physical	23.8	21.8	24.2	*23.3*
Sensory	28.7	23.5	24.8	*26.3*
Internal	26.9	24.9	28.2	*26.6*
Mental	20.8	16.8	18.2	*19.0*
Cognitive	30.1	29.0	29.0	*29.5*
Progressive	27.6	25.2	27.7	*26.9*
Other	24.4	21.4	24.4	*23.5*

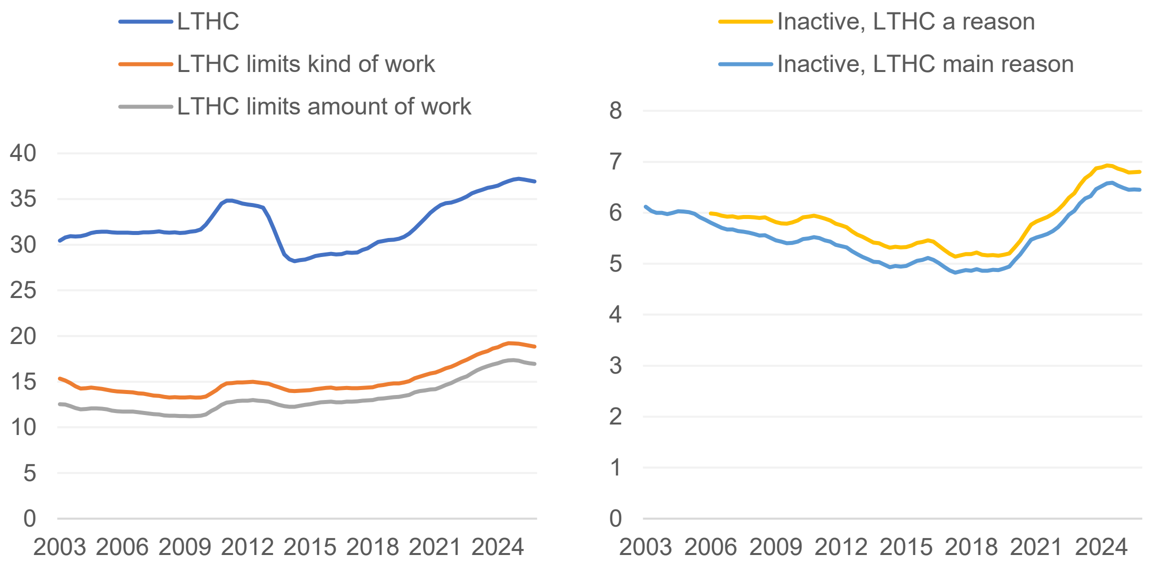
Source: LFS, authors' calculations.

Notes: Groupings of main health problem described in Appendix.

Appendix 5: Time series charts for measures of long-term health problems and related measures

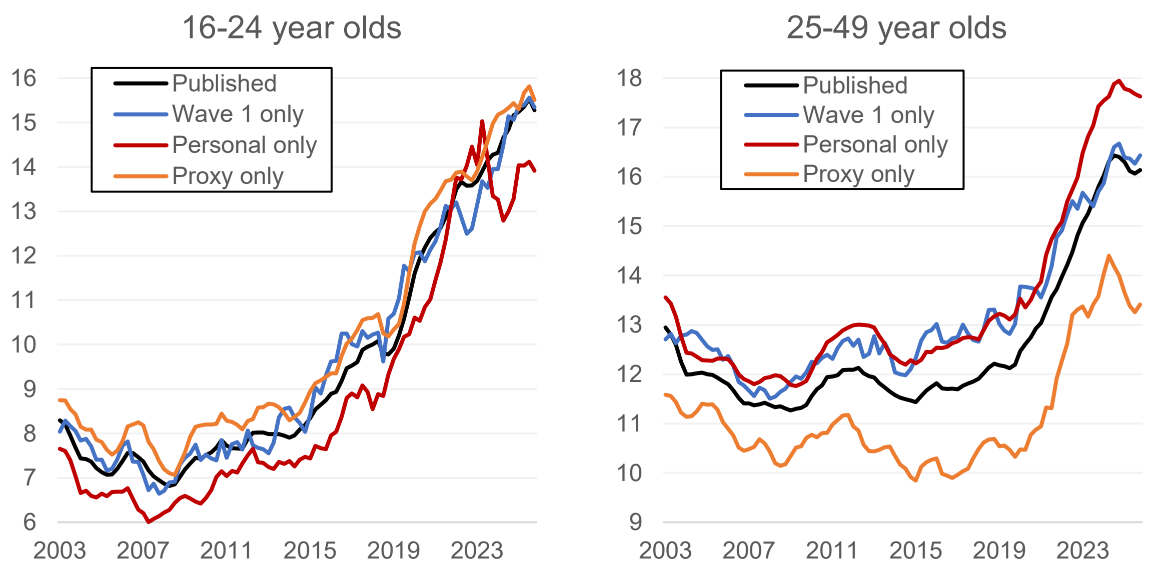
In the main text, Table 2 shows overall time trends for different measures, both for all ages and split by age group. In this appendix, we present some of the more detailed year-by-year trends in visual form.

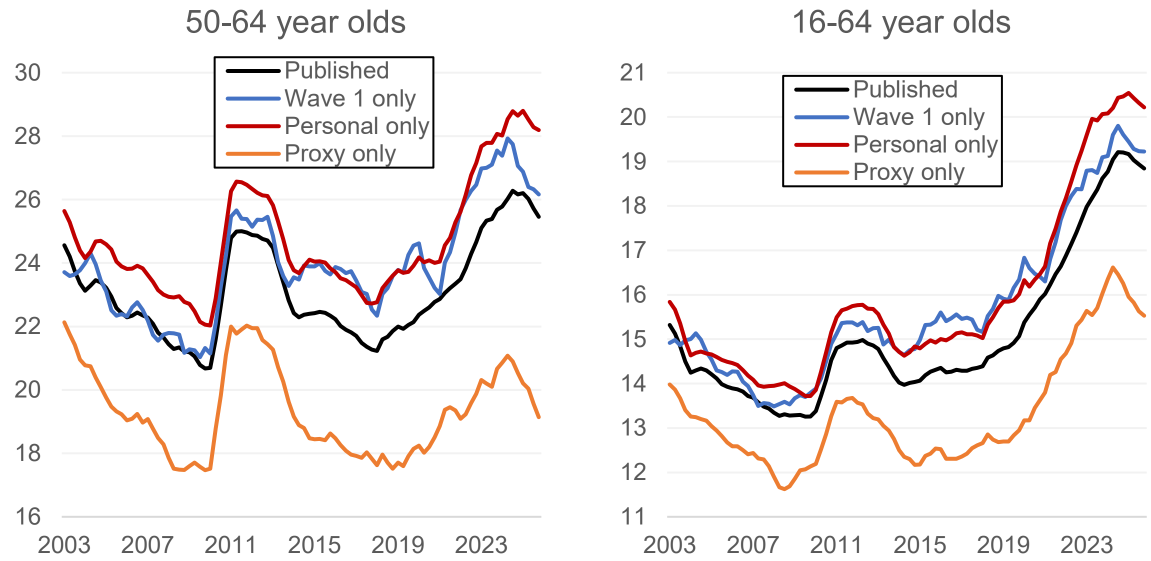
Figure A3 – Proportion of people aged 16-64 with long-term health conditions (variously defined) (%), four-quarter rolling averages, 2003 Q1 to 2025 Q4



Source: LFS, authors' calculations.
Notes: Proportions of the population. All use the full weighted LFS microdata. "LTHC" stands for "long-term health condition" – various measures as described in text. Four-quarter trailing rolling averages of non-seasonally adjusted data. Consistent with Table 3 in the main text.

Figure A4 – Proportion of people with kind-of-work-limiting long-term health condition (%), various cuts of data, by age group, four-quarter rolling averages, 2003 Q1 to 2025 Q4





Source: LFS, authors' calculations.
Notes: Proportions of the population. "Published" is constructed from LFS microdata rather than from ONS publication tables, but uses the full dataset and is thus consistent with the published data. The other lines use a subset of the data and are re-weighted to match population totals – see text for details. Four-quarter trailing rolling averages of non-seasonally adjusted data. Changes to LFS question routing in 2010 and 2013 change the propensity to report long-term health conditions, especially for older people. Consistent with Table 3 in the main text.

Appendix 6: Further analysis of the two-quarter longitudinal LFS data

In Table 5 in the main text, we explored the propensity for respondents to 'acquire' a long-term health condition between successive waves of the LFS – that is, not having a long-term health condition in the first wave, and having one in the next wave. We found that respondents who had proxy responses (X) in the first wave and personal responses (P) in the second wave were more likely to 'acquire' a long-term health condition, suggesting under-reporting of long-term health conditions by proxy responders.

Table A3 repeats this analysis for the opposite case of 'losing' a long-term health condition – that is, having a long-term health condition in the first wave, and not having one in the next wave. The XP reporting pattern leads to higher reporting of 'losing' a long-term health condition than the PP response pattern (which we assume most reliable), as it did for 'acquiring' in Table 5. This suggests some inaccurate reporting by proxy responders in both directions. However, the margin of 'bias' is larger for 'acquiring' (Table 5) than 'losing' (Table A3), such that the net effect would be for proxy responders to under-state long-term health conditions relative to personal responses.

There is also elevated 'losing' for the PX response pattern in Table A3 – that is, a personal response reports a long-term health condition, and a subsequent proxy response does not report a long-term health condition. This is consistent with elevated 'acquiring' for the XP response pattern (Table 5), but in the reverse order.

However, for both 'acquiring' (Table 5) and 'losing' (Table A3) there is no material bias in the case of "economically inactive due to long-term sickness (main reason)". That suggests that if the health condition is sufficiently serious to lead to economic inactivity, then there is little inconsistency in views between personal and proxy responders. So any bias induced by proxy responders seems principally to relate to the presence of less limiting health conditions.

Table A3 – Rate of losing a long-term health condition between successive quarters (%), by response pattern, different measures and time periods

	All persons			Employed in both quarters		
	2012-2019	2020-2024	Difference	2012-2019	2020-2024	Difference
Long-term health condition						
PP	4.2	5.0	0.8	4.4	5.3	0.8
PX	4.8	6.2	1.3	5.0	6.8	1.7
XP	5.0	6.8	1.7	5.3	7.4	2.1
XX	3.1	4.0	0.9	3.3	4.3	1.0
“Bias”: XP-PP	*0.9*	*1.8*	*0.9*	*0.8*	*2.1*	*1.3*
Work-limiting long-term health condition						
PP	2.4	3.4	1.0	2.3	3.3	1.0
PX	2.5	4.6	2.1	2.4	4.8	2.4
XP	3.0	4.4	1.3	2.8	4.1	1.2
XX	1.8	2.7	0.9	1.7	2.7	1.0
“Bias”: XP-PP	*0.6*	*0.9*	*0.3*	*0.5*	*0.7*	*0.2*
Economically inactive due to long-term sickness (main reason)						
PP	0.4	0.4	0.1			
PX	0.3	0.3	0.0			
XP	0.3	0.4	0.1			
XX	0.2	0.3	0.1			
“Bias”: XP-PP	*-0.1*	*-0.1*	*0.0*			

Source: LFS, authors’ calculations.

Notes: Uses pooled weighted data. Several quarters are missing as response type and/or health measure not available for one or both quarters in longitudinal LFS data: 2015Q1, all quarters or 2018, 2020Q3, 2020Q4, 2021Q3, 2022Q1. Response types: PP = Personal-Personal, PX = Personal-Proxy, etc. See Table 3 in the main text for equivalent results for ‘acquiring’ a health condition.