ECOLE DES HAUTES ETUDES EN SCIENCES SOCIALES

Master recherche en Sciences Sociales

Mention Sociologie Générale

Année Universitaire 2020-2021

Condemned to Leisure:
Time use during the first UK lockdown in Spring-Summer 2020

Mémoire de Master 2

par James Alster

sous la direction de Serge Paugam

Septembre 2021

Abstract:

The maintenance and dissolution of pre-lockdown habits of time use during the first UK lockdown of 2020 are examined through the perspective of reactions to *anomie*. Time-use survey data collected during lockdown restrictions are compared to survey waves from before lockdown in 2016 and in August 2020 as many restrictions were eased. The results show the impact of shifting obligations of work and unpaid work, in particular as regards male-female inequalities in distribution of unpaid work and time fragmentation, and class inequalities as regards working from home. Also apparent, however, are differences in the attribution of free time that are attributable to responses to *anomie* patterned by educational level, as regards the intensity of leisure activity engagement and the synchronisation of schedules between household members, as well as a global homogenisation of waking and sleeping times on workdays and non-workdays.

Table of Contents

Introduction

The first UK lockdown began on 23rd March 2020 when the Prime Minister ordered people to ‘stay at home’, with legal measures coming into force on the 26th. Restrictions began to be phased out on 1st June 2020, and by mid-August most had been lifted, although in a sense lockdown has never properly ended: some restrictions remain in place at the time of writing in June 2021.

At the risk of sounding trite, lockdown was an unprecedented curtailing of everyday freedoms which deeply affected the whole of society. Its immediate impact and long-term ramifications will no doubt be studied by sociologists for years to come. The present study explores one aspect of the social effects of lockdown, that of everyday time use.

The dataset used, *United Kingdom Time Use Survey Sequence Pre and During COVID-19 Social Restrictions, 2016-2020* (Gershuny and Sullivan 2021), is an excellent opportunity to examine the effects of lockdown. Using a new digital method of data collection (described in Sullivan et al. 2020), two waves of time use survey data were collected during lockdown restrictions, in June and again in August 2020. The particular interest of this dataset is that precisely the same method was used in a wave collected in 2016, allowing direct comparison of time use before and during lockdown.

Originating in the early twentieth century, time use surveys have been an established part of sociology since Szalai’s (1972) pioneering international study. Respondents fill in a ‘time diary’, indicating what activities were done when during the day, which enables sociologists to take everyday use of time as an object of research. Studies have mostly focused on deriving the quantities of time spent in activities, in order to examine the ‘balance’ between work, housework and leisure time, as well as inequalities of time use. Recent reviews can be found in Cornwell et al. 2019 for the English literature, and Chenu and Lesnard 2006 along with Bouffartigue 2006 for the French.

The present study, however, does not ask the question of work-life balance. Instead, use of time in lockdown is seen as characterised by *anomie*, a lack of regulation by social norms.

When many daily activities were forbidden in (what was perceived to be) a novel social situation, conventional norms governing time use and daily routine became less relevant. The question of what to do during the day suddenly became much more open, especially for those who were no longer working. Responses to this *anomie* were shaped by a variety of factors. On the one hand, a decrease in institutional obligations such as work came with an increase in other obligations, in particular childcare, inequalities in which reshaped typical daily schedules. On the other, time newly freed from obligations was used in ways patterned by social classes' different approaches to time use: shifts can be observed in the number and kinds of leisure activities, as well as the daily scheduling of activities and synchronisation between household members.

In the following sections, the theoretical background, dataset and methodology used are outlined in more detail, before the main analysis. The analysis looks firstly at the overall structure of daily routine, contrasting 'typical' days both before and during lockdown; a second section turns to the fragmentation of activities throughout the day, both in terms of activity periods and multitasking; the third takes a more detailed look at leisure activities, a fourth at the timing of waking and sleeping, and finally the question of time spent with other people is considered. Relations between several aspects of time use and a mental health indicator are also examined at various points.

1. Theory: Lockdown and responses to *anomie*

1.1 Condemned to Leisure: *Anomie* in Lockdown

The first UK lockdown that started on 23rd March 2020 was an unprecedented restriction of everyday freedom. Work, study, travel, socialising in person suddenly became off-limits to many. But the loss of freedom was also, in another sense, a gain. Before lockdown, people had been obliged to spend a large portion of their time in institutional settings such as work. But all of a sudden, for the many who found themselves unemployed or on furlough, that was no longer the case. Confined to their homes, they were liberated from the obligation to be somewhere for a large portion of the day. They suddenly had a large amount of free time that, within the restrictions of lockdown, they could spend however they wished.

But this new free time was different to free time before lockdown. Before lockdown, free time and leisure activities had been found in the gaps of a daily schedule otherwise filled with time-consuming obligations such as work, childcare and housework. In Lefebvre's words: "Leisure seems therefore to be the not-everyday in the everyday… we work in order to earn free time, and leisure has only one meaning: an escape from work" (*Critique of Everyday Life I* 1958, 49-50). This free time is the opposite of work, and in some sense its recompense. At work, you do not have control over how time is spent, but free time is time that can be spent as you like (at least in theory). Free time gets its meaning and purpose from what it is not: work, and its unfreedom and unpleasantness. It is the escape from the mundane limitations and obligations of the everyday workday.

Moreover, as Adorno argues in his essay *Free Time*, not only is free time "shackled to its opposite" (2001 [1977], 187), but the typical leisure activities in which it is spent, such as hobbies and foreign holidays, appear pointless unless seen as a way to pass time that is not work. People do these activities precisely because they are 'what people do when not working'. There are societal norms about how to spend time when not at work, which prescribe leisure activities such as the cinema and camping trips. When people put their feet up in front of the TV after a day at work, their behaviour is framed and given sense by these norms.

Free time in lockdown was different. In lockdown, work and many of the other activities that made up the day were no longer possible. In a situation similar to the unemployed, people were 'condemned to leisure' (in the phrase of Wilensky 1963). Free time became no longer the 'not-everyday in the everyday', but just the everyday. It had lost its opposite from which it was the escape. A result was that leisure activities, which draw their meaning from social norms of appropriate ways to spend time when not working, no longer had a rationale. There were a lack of norms relevant to how to spend free time, and what it was 'for'.

In this way, free time in lockdown was similar to what Gunter and Gunter term 'anomic leisure' (1980, 369-370), referring to Durkheim's concept of *anomie* in *Le Suicide* (1897). They see the free time of the unemployed as characterised on the one hand by a lack of structural constraints and on the other by subjective disengagement from activities. I would suggest that the latter is at least partly caused by the former: the stigma attached to a lack of work means that social norms governing unemployed time use encourage work-seeking activity and do not reinforce subjective engagement in idle leisure. This is a feature of the 'weary community' described in Johoda, Lazarsfeld and Zeisel's classic study *The Unemployed of Marienthal* (1988 [1933]). In lockdown, this experience of 'anomic leisure' suddenly became generalised from the unemployed to a far larger proportion of society. The degree of stigma involved was relatively ambiguous compared to the pre-lockdown unemployed, but the lack of structure and guidelines was even more complete.

The lack of social norms governing time use did not apply only to leisure activities. With the loss of daily work routine, the question of how to spend time at any given point in the day became open: all time became potentially free time. Housework no longer had to be slotted in at a convenient moment; an afternoon nap was now a regular possibility; work-from-home allowed more flexible hours. On the other hand, the obligations of childcare increased with the closure of schools, to become a constant and limitless demand on time use. Many previous norms governing all forms of time use were no longer applicable. Lockdown time – especially in the first lockdown of 2020, when there had been no time for new norms to become established – was typified by a 'normlessness', where the question 'what to do?' was far more open than before.

I wish to argue that this normlessness, *anomie* – as well as its counterpart, 'fatalism' – is a concept that is central to understanding time use during lockdown. But the concept needs definition, since Durkheim's original exposition of *suicide anomique* (1897) is inconsistent, and the term *anomie* has been used since by many social theorists with contradictory and sometimes vaguely defined meanings. Here I follow Besnard's re-definition (1993), which seeks to clarify Durkheim's usage. *Anomie* is a lack of regulation of the individual by social norms. The individual finds themselves presented with a seemingly limitless range of norm-approved options for action. Its opposite is 'fatalism', which is an excess of regulation by social norms: the individual is pressed to internalise guidelines for behaviour that they are unwilling to accept.

Perhaps the most obvious application of this pair of concepts to lockdown is not in fact *anomie*, but fatalism. Fatalism is one theoretical way to explain the suffering and mental health consequences of *déclassement*, and was used by researchers in the 1960s to explain high rates of suicide in the unemployed (Besnard 1983). The concept continues to be used in more modern research, such as Paugam's theory of *disqualification sociale* where part of the suffering and difficulty of unemployment is the pressure to assume the stigmatised identity of someone who needs to be assisted (Paugam 2009 [1991]). Fatalism can accordingly be a tool to explain the difficulty of the experience of lockdown. New norms of behaviour, subjectively seen as unacceptable, were imposed on people: for instance, those suddenly told that they were not an 'essential worker' and could not therefore work, or that they must become a housewife in order to take on childcare responsibilities.

The other side of the coin in lockdown, however, was *anomie.* Lockdown imposed a novel social situation, without easy or familiar precedent, and suddenly there was a lack of social guidance on what to do. Drifting without the moorings of daily routine, people had to construct their own justifications for how to spend time – or just do something, or nothing. Activities were deprived of the structure, meaning and rationale that they previously had, both as regards their timing, and often too their content, the latter particularly the case for leisure activities.

It is worth making a distinction here. What has been described so far is what Besnard (1993) calls ‘acute *anomie*’: a temporary lack of guidance by social norms following a change in circumstances. But there is also ‘chronic *anomie*’, a continuous state of society failing to provide norms guiding action. Rather than a situation in which customary norms have become inapplicable, chronic *anomie* is the continuous relevance of a norm that there are no norms, that is, an ideology of unlimited choice. To the extent that this is a feature of contemporary UK society, it is possible to see lockdown as a moment of acute *anomie* in a context of chronic *anomie:* a general lack of norms for action was redoubled by new circumstances.

It would be misleading to imply that the experience of lockdown was the same for everyone. Despite the seemingly universal reference of ‘stay at home’, lockdown was nevertheless an unequal restriction, justified in the name of a universal public good, whose effects varied widely by social group. Among other inequalities, hospitality, retail and construction workers, for example, were far more likely than IT workers, lawyers and medical professionals to lose income if not their job. Work schedules varied from a long work-from-home-day to part time shifts, while ‘essential workers’ often found their work schedules increasing in length and intensity. Young people entering the labour market for the first time found that there were no jobs to start. The closure of schools shifted a huge amount of childcare back onto the family, where the burden was often unequally distributed (Cominetti et al. 2020, Brewer et al. 2020, Blundell et al. 2020, Sevilla et al. 2020).

The nature and degree of *anomie* experienced by these different social groups varied greatly. Most importantly, there was a big difference between those who stopped work and those who did not. For the latter, although there was more continuity in that the day still revolved around working hours, the place and relation of activities in the day was still transformed. Outside leisure and socialising was heavily restricted, and those working at home worked in new conditions, while the closure of schools disrupted families’ daily routine. A useful perspective through which to see the variety of situations is that of Jacobs and Gerson in *The Time Divide* (2004), who, in a pre-lockdown context, show the difference in time use between overworked salaried workers with too little time, and under-employed workers on an hourly wage with too much. In lockdown, many workers shifted from one to the other, as they stopped work or were suddenly deemed ‘essential’, while many others had these situations intensified, as the un- or under- employed found themselves in a shrinking job market, and the overworked had were loaded with increased obligations of housework and childcare. All of these groups, however, experienced a degree of *anomie* as the changing demands on their time disrupted or made irrelevant previous daily routines.

The concept of *anomie,* as well as ‘fatalism’, has usually been used as an explanation of mental suffering or suicide, as in Durkheim, or of crime and delinquency in the (rather different) theory of *anomie* proposed by Merton (1968). These theories use the lack (or excess) of social regulation to explain psychological suffering and ‘deviant’ behaviour. But I would like to take *anomie* elsewhere. Time use in lockdown was typified by the lack of relevance of previous norms; how did people respond, and what explains their response? How did they fill the gap, and what was the degree of continuity and of innovation in time use? Time use is influenced by many different aspects of society, from institutions such as work and school, to housework and childcare, to family and household relations, to learnt practices of time scheduling, as well as to the patterning of cultural practices such as leisure activities. As such, the effects observed in the *anomie* of lockdown have complex explanations. The most prominent factors explaining time use in this study are outlined in this section, broadly grouped into two: changing obligations on time use, in particular those deriving from the institutions of work and school; and approaches to the use of free time, which appears as a cultural practice largely conditioned by education and upbringing. All of the factors, however, combine in complex ways to produce patterns of time use in the *anomie* of lockdown, and their effects are seen throughout each of the analysis sections that follow.

1.2 Explaining Time Use in Lockdown: Changing Obligations

The first group of factors shaping time use that appear in this study are changes to obligations. Everyday time use, at least outside of lockdown, is in large part determined by societal institutions, in particular work and school, that place substantial demands on people. These institutions demand time commitments that are not only very substantial but also often scheduled, and occupy a fixed place in the day, around which other activities are fitted in to create a daily schedule (As 1978, Southerton 2006).

In the case of work, work time obligations are closely linked to class position, because different occupations and forms of employment make different time demands. Javeau pointedly observed that the prototypical nine-to-five workday is “more a normative model than a Weberian ideal-type” (1983, 73). The fact of working a night shift, for example, is linked to social status, and has implications for class position by virtue of the others with whom that activity is shared. Recent research provides empirical backing: Chenu and Robinson (2002) and as well as Lesnard (2009) have shown a relationship between non-standard work hours and class position in France; while in America Jacobs and Gerson (2004) have shown that there is a ‘time divide’ in daily schedules, between those working nominally ‘9 to 5’ salaried positions five days a week, who find themselves increasingly overworked, and the large proportion (as many as 40% of Americans according to Presser 2003) who work non-standard hours. Lockdown will have transformed this picture, as work demands increased for many essential workers, shifted to the context of home for others (usually the more qualified) and in many cases stopped entirely, whether because of furlough or unemployment.

Educational institutions also affect daily time use, not only for students (who are excluded from this study, see section 2.1), but most notably by removing children from their parents’ care for a large proportion of the day. When schools closed, families – and in particular, mothers – had to care for their children all day long. Moreover, mothers are increasingly seen, and see themselves, as responsible not only for physical care but their child’s entire cultural and educational development, as part of what has been termed ‘concerted cultivation’ (Hays 1996; Lareau 2003). The closure of schools will have redoubled this burden, as families did not only have children on their hands for more time, but their education as well. Another form of obligation, if not so determined by societal institutions, is that of housework, which confronted those stuck at home at a moment when, for those who could afford it, it could no longer be done by hired, usually female labour. It has been well documented by a long tradition of research on the distribution of unpaid household labour (see reviews in Cornwell et al. 2019, 306-308; Bouffartigue 2006) that both the obligations of childcare and housework are unequally shared between men and women, falling principally on the female members of the household (most recently, see Man Yee Kan et al. 2011, Altintas and Sullivan 2016, Pailhé et al. 2020).

The obligations of work, as well as of childcare and housework, shifted during lockdown. While previous studies (e.g Sevilla et al. 2020, Cominetti et al. 2021) have established the outline of these effects in lockdown using large-scale questionnaires, this study looks in detail at the ramifications for daily time use, most notably by comparing daily schedules (section 3). Not only may there have been a removal, shift or expansion in the parts of the day devoted to these activities, but there will have been a knock-on effect on the entire daily schedule, as changing obligations placed in question the overall structure, timing and relation of activities in the day.

Moreover, the obligations of work, childcare and housework impact time use in another way: the fragmentation of the day. Rosa in *Social Acceleration* (2013), as part of his wider thesis on the acceleration of life, sees a constant external demand for individual availability as a feature of modern time use. This demand can come from the extension of shift work and the gig economy (cf. Kalleberg 2011) along with the increase in out-of-hours communication enabled by technology such as smartphones that obliges workers to make themselves constantly available. More importantly for this study, it can also come from the home and family, in the form of the ever-present 'mental load' of housework and childcare, particularly of young children. This constant external demand to be available has the effect of interrupting other activities, fragmenting the day, which is visible in time-use surveys as the fragmentation of activity periods or by entering a secondary, contemporaneous activity. Previous time-use research has focused on the demands of housework and childcare, time fragmentation, and the implications of this for male-female inequalities, particularly between parents (Sullivan 1997, Sevilla et al. 2012, Sullivan and Gershuny 2018). These inequalities may have been reconfigured during lockdown, as burdens increased, men as well as children were more present in the home, and – for tasks without a fixed time – the *anomie* of the day may have allowed a certain amount of manoeuvre as to the degree of fragmentation.

1.3 Explaining Time Use in Lockdown: Use of Free Time

The second group of factors that explain patterns in lockdown time use observed in this study relate to spending free time. Once the obligations of work, childcare and housework have been accounted for, the rest of time use is more a matter for individual discretion (cf. As 1978, Southerton 2006). As argued above, the disruption to daily schedules in lockdown and the forbidding of many activities created not only a generalised *anomie* concerning the daily schedule, but a particular uncertainty as to the place and purpose of leisure activities.

In this study, spending free time appears to be a cultural practice, patterned by educational level, and, by implication, greatly determined by upbringing. This is most obviously the case for leisure activities, in both content and their timing. Sleep, eating and self-care, meanwhile, although needs, are also on the one hand patterned by educational level in ways similar to leisure activities, while are affected on the other by the *anomie* of daily schedule.

The first factor here is a propensity to schedule the day into clearly defined periods. This is a form of time management, instilled by the educational system. At school, children's future life chances are affected by the extent to which they internalise norms of scheduling (Henri-Panabière et al. 2019). The echoes of this upbringing resound throughout society, as the '9 to 5' school day becomes the '9 to 5' workday, and the regular daily rhythm learnt as a child is reinforced by daily work schedule – for those successful enough to make it in the higher qualified jobs associated with such a schedule (Jacobs and Gerson 2004). "The more one 'rises' in the social hierarchy, the more chances one has to find temporal socialisation in sync with the educational institution scheduling of time (*rapport scolaire au temps*) and authority" (Darmon et al. 2019, 14). The circle is closed by the knock-on effect on family schedules as lower qualified workers working variable and non-standard shifts do not pass on norms of regular daily routine to their children (Presser 2003; Millet and Thin 2005), while more educated parents supervise homework activities and behaviours such as the structuring of leisure time, as part of 'concerted cultivation' (Hays 1996; Lareau 2003).

The scheduling of daily activities is therefore a cultural practice, one aspect of society's class structure. In lockdown, where norms of time use became less relevant and daily routines were disrupted, it might be expected that those used to scheduling their time continued to do so, re-applying norms of regular time use to maintain daily structure even in the absence of many customary activities.

A second feature is not so much the timing, as the content of specifically leisure activities. This is again affected by education and early life socialisation, and has been identified as a key aspect of social class ever since Bourdieu's *La Distinction* (1979). Recent time use research has focused on Peterson's (1992) modification, arguing that cultural tastes – and so, in this context, leisure activities – are no longer each associated with a particular class position, but that cultural omnivorousness (as opposed to having a limited range of tastes) has become the key variable. Southerton (2006) and especially Sullivan and Katz-Gerro (2007) find that 'voraciousness' – a time-use equivalent to omnivorousness, measuring the number of different leisure activities done in a day – is associated with educational level. It has been observed that the most affluent and high status individuals, the 'harried leisure class', have the least free time (Linder 1971, Gershuny 2005), and so for these individuals a particular high-status leisure activity, or a voracious variety, may be a way to reconcile social status and the limited time available. Moreover, Rosa (2013, ch. 7) suggests that intense and time-pressured leisure consumption may be visible in time-use surveys in the form of activity fragmentation, as the seemingly limitless possibilities of worthwhile cultural consumption offered by modern society (cf. Besnard's notion of 'chronic *anomie*', section 1.1) drive individuals to consume as many of them as possible in the "Sisyphean task" (p. 184) of not missing out.

While these leisure practices can be seen as greatly determined by early life socialisation, there is also the possibility that they can be engaged in actively in order to accumulate cultural capital. Bourdieu in the *Pascalian Meditations* draws a contrast between leisure where nothing is at stake (*en jeu*) and leisure which is implicated in the sphere of social competition: "in fact, without special effort, 'free time' escapes only with difficulty from the logic of investment in 'things to do' which, even if it does not reach the point of explicitly worrying about 'making a success of your holidays', according to the precepts of women's magazines, extends the competition for the accumulation of symbolic capital into many varied forms" (2003). Moreover, some theorists offer a complimentary 'use' of leisure activities. Building on Foucault's notion of the 'entrepreneur of the self' (2004, 232) they see modern society as an 'achievement society' (Han 2015, 8), in which everyone tries to self-realise through excellence in both work and leisure activities, constructing identity through a strategic life plan (Giddens 1991, 85-87), and managing uncertainty over future life chances (Beck 1992). Intense and varied engagement in high-status leisure activities are thereby seen not only as accumulating cultural capital, but as part of an active project of self-development and perfection (Binkley 2009).

Spending the free time of lockdown in a wide variety of leisure activities and high-status pastimes could therefore be seen not only as the result of cultural habits determined by early life socialisation, but as an active attempt to accumulate cultural capital and manage the risk concerning future life chances that will have increased in lockdown. There is already evidence in France for a diversification of leisure activities during lockdown, especially among the less educated (Jonchery and Lombardo 2020). On the other hand, this point of view could seem *misérabiliste* ('intellectually elitist'; cf. Grignon and Passeron 2015 [1989]), in that it assumes that the ranking of leisure activities necessarily reflects that of the dominant social group(s), and that all members of society, when engaging in high status or a variety of leisure activities, are 'using' it in order to accumulate cultural capital. The *why* of leisure activities is largely inaccessible to a time use study which necessarily categorises them into broad groups, and where detailed qualitative data is not available. This perspective, however, seems a plausible explanation of the trends observed, and so is retained here, even if verification that leisure activities are in fact 'used' in this way must await more detailed qualitative studies.

Sociability also has many aspects of a cultural practice, since as Héran showed (1988) it is strongly patterned by educational level, something that more recent studies of social homophily have continued to support (McPherson et al. 2001, Bidart et al. 2011). As discussed above, less educated workers are more likely to have non-standard work schedules, and Presser (2003), Lesnard (2008, 2009) and Lesnard and Kan (2011) have built on this to establish that family schedules are often desynchronised. Lambert et al.

(2020), hypothesised without time use data available that families, in particular working class families, freed by lockdown from the imposition of non-standard work schedules, re-synchronised their daily lives to increase time spent with other family members. Their response to the *anomie* of lockdown would accordingly be to regain family time.

1.4 Lockdown Time Use and Mental Health

There are many ways in which lockdown may have impacted mental health for the worse. Most obviously, stopping work, becoming unemployed, financial uncertainty, the lack of social contact, physical isolation may all have contributed to poor mental health (Blundell et al. 2020; Public Health England 2021). Moreover, as mentioned above (section 1.1), the pressure to internalise norms seen as unacceptable, may also provide a 'fatalist' explanation of poor mental health in lockdown.

In this study, moreover, some aspects of time use appear specifically linked to mental health. The first of these is the maintenance of daily routine. In Lefebvre's perspective, 'the everyday' is a very artificial construction, filled with the products of industrial capitalism and insulating people from inequality and oppression. But artificial though it may be, for the people who live it the everyday is the epitome of normality, a comforting point of reference. "The everyday, established, consolidated, remains the only reference for common sense" (Lefebvre, 'Quotidienneté', *Encyclopedia Universalis*). In a moment of change, crisis and widespread uncertainty such as lockdown, everyday routine was something that could provide a sense of continuity and stability, and as such may be linked (if reciprocally) to mental health.

Meanwhile, Han in *The Burnout Society* (2015) links poor mental health to two aspects of life which may be indirectly measured in time use surveys. The first is time fragmentation. Han describes a scattered mode of awareness, in which people constantly react to a never-ending succession of stimuli from external activities, whether work or leisure consumption, in a form of hyperactivity. This may appear as activity fragmentation or multitasking in the time use survey. Secondly, Han argues that overwork, not only in paid work but also as over-commitment to leisure activities, can cause a depression that occurs when "the achievement-subject is no longer able to be able” (2015, 11). This may be a consequence of the forms of competitive leisure consumption mentioned in the previous section, although without detailed qualitative data available confirmation of a link will have to await more detailed studies.

2. Data

2.1 Survey

The dataset used in this study is the *United Kingdom Time Use Survey Sequence Pre and During COVID-19 Social Restrictions, 2016-2020*, in the form made available on 21st January 2021 (Gershuny and Sullivan 2021). It was commissioned by the Centre for Time Use Research at the University of Oxford,[1] and at the time of writing has so far been used in only one previous study, a brief report on the prevalence of 'high-risk activities' from the point of view of Covid-19 transmission (Gershuny et al. 2020).

The survey data was collected in three waves: 2016, June 2020 and August 2020. The 2016 wave is a mixture of data collected in the periods 1st – 8th February (405 diaries), 12th – 19th October (252 diaries), and 15th – 19th December (354 diaries, for a total of 1011 diaries). The wave labelled in the dataset 'June 2020' was collected between 19th May and 8th June 2020 (1005 diaries), while 'August 2020' was collected between 31st July and 28th August 2020 (987 diaries). 27 additional diaries from the 2016 wave with unknown date were excluded because this information is necessary for the weighting (see section 2.2. below).

A total of 3032 24-hour time diaries were collected from 1575 respondents over the three waves. The respondents were different in each wave, which obliges looking at demographic shifts rather than attempting a longitudinal analysis of respondents. Each respondent filled out between one and three diaries in a survey wave (a very few completed four diaries): details are in Table 2.1.1.

Table 2.1.1

Number of Diaries	**2016**	**June 2020**	**August 2020**
1	404	140	92
2	197	108	119
3	76	217	219
4	3	0	0
Total respondents	680	465	430

1 https://www.timeuse.org/

Total diaries	1038	1007	987

The timing of survey waves provides a fascinating comparison between three relatively distinct periods: a pre-lockdown reference, a period of close to full national restrictions, and a period of relative easing, while some restrictions still remained in force. During the May-June survey wave, most of the lockdown restrictions imposed in March remained in force, such as the closure of non essential shops, and a restriction on leaving the home for non-essential activity. Outdoor recreation had been permitted, however, since 13th May. Lockdown was eased further on 1st June: the restriction on going outside with replaced with a requirement to be at home overnight, people were permitted to meet outside with up to six people and the phased re-opening of schools in England began. These changes will have had a slight impact on the 'lockdown' results for June 2020. During the August survey wave, almost all lockdown restrictions had been lifted (on 4th July), except those on gatherings of over 30 people. Hospitality businesses were allowed to reopen. While some local lockdowns were sporadically imposed during August, the government was encouraging outdoor activity with its 'Eat Out to Help Out' scheme, while lockdown was loosened further: indoor recreational spaces such as theatres and bowling alleys were allowed to open on 14th August. The re-tightening of restrictions in anticipation of the autumn 'second wave' did not begin until 14th September.

The diary data was collected with the recently developed 'Click and Drag Diary Instrument', described by Sullivan et al. (2020). Briefly, respondents were invited to click and drag on a horizontal bar representing a 24 hour day from 4am to 4am to indicate the time spent on an activity, and then to fill in the activity code from a list of 36 options, as well as having the option to write it in manually (the small number of written-in responses, < 0.1% of the total, were not available in this version of the dataset.) These responses are the information concerning primary activity. The process was repeated for a secondary activity, and then the respondent was prompted to fill in four further fields for each primary activity period recorded: subjective enjoyment, device usage, location, and who the activity was done with (up to four people could be indicated simultaneously). Respondents filled out one such diary on an initial day, and then on a number of further days randomly chosen by the software.

Sullivan et al. (2020) compare the results of this new methodology with the conventional 'gold standard' time diaries done by paper questionnaire, such as the *United Kingdom Time Use Survey, 2014-2015* (Sullivan and Gershuny 2015). They find that the reduced labour involved in the digital questionnaire format decreased non-response, and greatly decreased researcher labour time, while not apparently affecting the quality of the results.

My own comparative analysis of the click-and-drag dataset with the 2014-2015 survey did nonetheless indicate a slight loss of quality in three regards. Firstly, only 36 activity codes are offered, in comparison to the several hundred coded by researchers for the earlier survey. Secondly, the non-response for secondary activity is higher, at around 80% rather than around 70% (possible reasons for non-response in this diary field are considered in section 5.2). Thirdly, the average duration of an activity period is much longer in the online compared to the written version: fewer periods are entered per day. Since these differences are as much the case in the 2016 wave of the dataset analysed here as in the waves carried out during lockdown, it seems that the difference is due to the survey methodology, not lockdown. The 2014-2015 survey is therefore not directly comparable to the one used here.

In addition to the diaries, each respondent filled out a detailed questionnaire, with additional questions added for the waves in 2020. The details exploited in this study are demographic information (sex, age, educational level, social class), employment status and its change into lockdown, and a mental health assessment questions, subjectively assessed into lockdown. These questions and the coding of their responses into variables are discussed in section 3.3.

2.2 Sample Representativeness and Weights

The analysis in this study takes as its object the UK population aged 18-65, excluding students. Students and retirees over 65 have a different relationship to time by virtue of their limited participation in the labour market. They were accordingly excluded to simplify the analysis, while survey itself did not include respondents aged under 18. Excluding these 449 respondents (including 30 where age or day of the week is NA, making their case weight *NA*) gave a final sample of n = 2583 diaries (754 in 2016, 893 in June 2020, 936 in August 2020).

The original sample was designed to be nationally representative as to age, sex, region and social grade (a classification by occupation into 6 groups, as defined by the National Readership Survey[2]), and weighting is provided to correct for imbalances in the sample. It is nevertheless deficient as regards the quota in two respects. Firstly, the social grade group C2, skilled manual workers, are under-polled in the two 2020 waves of the study compared to the survey specification, at around 10% of the (weighted) sample rather than 20%, while group AB, managerial and professional occupations, are 35% rather than the desired 25%. The analysis in general controls for social class in order to somewhat correct for this effect. A second, smaller, issue is that London only represents 10-11% rather than the optimal 13% in each wave.

More serious are deficiencies in aspects not included in the survey quota. It is far from ideal that it is not necessarily representative by ethnicity. Inter-ethnic inequalities continued in lockdown, as evidenced in worse mental health, decreased community interaction, higher rates of Covid-19 symptoms, and more key workers (Nandi and Platt 2020). It is in particular very unfortunate that this survey does not even contain an ethnicity variable that would permit such inequalities to be estimated. Secondly, only 2% of respondents have 'no qualifications' (less than GCSEs) in the survey, much below the national average of 6.5%.[3]

Two weights are provided, '*crudewt*' which corrects over days of the week, and '*crudewt2*' which additionally corrects over age groups. In the initial sample the distributions of these two variables are very far from corresponding to the ideal, as can be seen in Figure 2.2.1 which shows the distribution of weekdays in the weighted and unweighted sample (the sample excluding students and those aged 65+ is in blue). The random day sampling produced far fewer weekend days in the 2016 wave, for which the weighting corrects.

2 http://www.nrs.co.uk/nrs-print/lifestyle-and-classification-data/social-grade/
3 https://www.nomisweb.co.uk/articles/1196.aspx

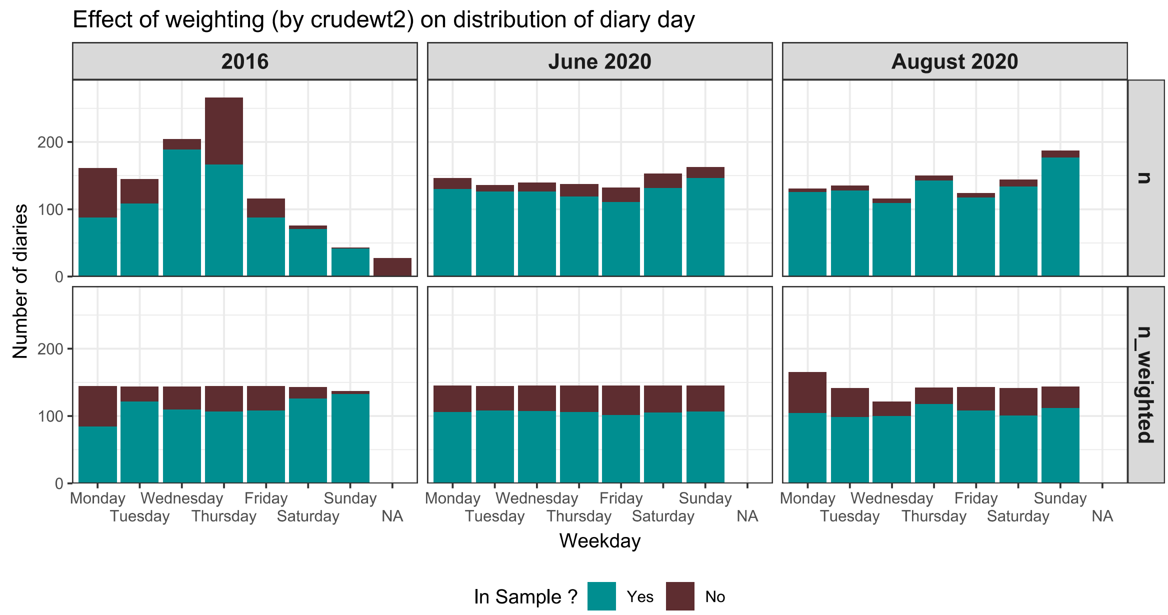

Figure 2.2.1

Moreover, Figure 2.2.2 shows that the 2020 waves greatly undersampled aged 18-24 and 65+, while the age group 25-35 was oversampled. The imbalance can be partially corrected by the exclusion of students and those aged over 65, but without weighting still remains far from the quota distribution that is produced by using *crudewt2*.

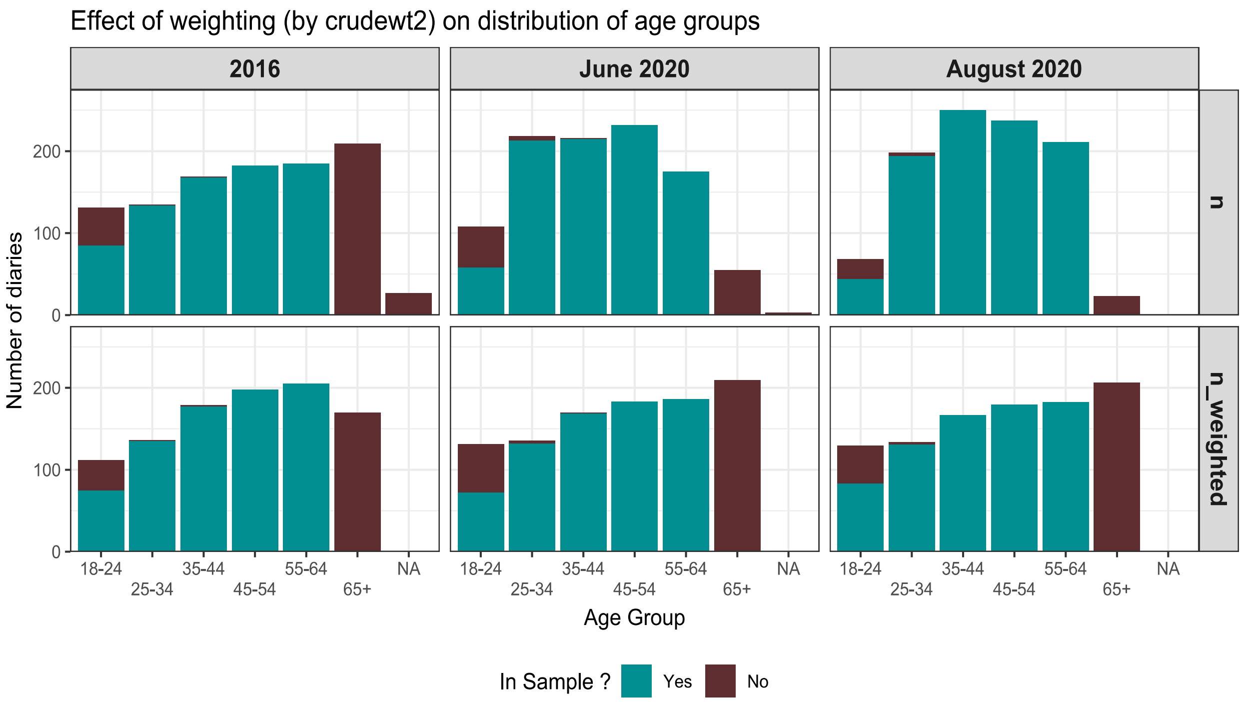

Figure 2.2.2

The corrections produced by weighting demonstrate that it is necessary use weighting both across weekdays and across age groups in order to ensure a degree of national representativeness. It was accordingly decided to use *crudewt2* in all analyses. There are some issues, however. Firstly, the documentation provided with the survey (Gershuny and Sullivan 2021) advises against using *crudewt2* for inferential statistics, because 38 values are very high, above 4. But this is mostly due to the very low numbers of respondents aged 65+ in the 2020 waves: excluding those aged 65+ reduces this to only one weight above 4, mitigating this issue. Secondly, the exclusion of many highly weighted cases, in particular those aged over 65, reduces the mean of the weights from 1 to 0.88. This will lead to some distortion as weights' relative distance from the mean has changed. Low weights' distance from the mean has been reduced by a greater proportion than that of high weights, and so their weight in the analysis will no longer be sufficiently reduced, relative to the highly weighted cases. However, without weighting these cases would have a far greater relative weight, so on balance use of the weights for the reduced sample is still important to maximise the representativeness of the analysis.

2.3 The Sample and Changes in Work Status over Lockdown

Given the great shifts in the labour market that took place over lockdown, it seems appropriate to look at the shifts in employment status of the respondents in the 2020 survey waves. This gives an overview of the relative rates of job loss which are important background to the results of the study, as well as allowing a check of the extent to which job loss in the dataset is representative of the wider UK population.

Figure 2.3.1 shows the change in work status in lockdown, as a percentage of all diary respondents who were in work before lockdown. Around 25% of all pre-lockdown workers had become unemployed or stopped work on furlough in June 2020; this decreased to around 10% in August. It can be seen that furlough decreased across the board in August 2020 compared to June 2020, replaced by a mixture of re-hiring and part-time contracts. Loss of employment and furlough rates are higher for women compared with men, 18-24s and (in June 2020) 55-64s compared to other age groups, those without a university degree compared to those with, and lower qualified compared with higher qualified jobs. The high rate for 'Intermediate' occupations in June 2020 is because that category includes the self-employed (see Appendix A).

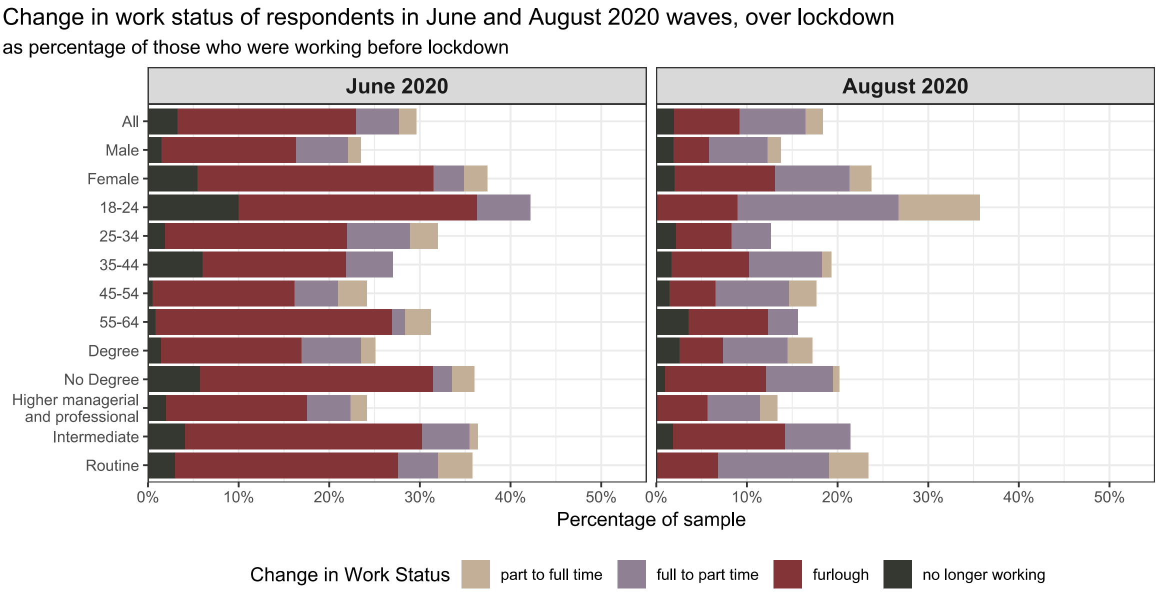

Figure 2.3.1

These figures are very similar to those in larger specialised studies, providing reassurance as to the representativeness of the dataset in this regard; directly comparable are the graphs of Cominetti et al. (2020, 30), for June 2020 based on a sample size of over 10 000, and Brewer et al. (2020, 30) for September 2020 based on a sample size of 6000. The main disparities are: in this study the male-female disparity in job loss is somewhat greater than those of Cominetti et al. (2020) and Brewer et al. (2020), and the job loss for those with no degree is underestimated here because of the low sampling of those with no qualifications. Brewer et al. (2020) also have slightly higher figures for unemployment across the board, since job losses spiked when the furlough scheme changed at the end of August, after the end of the present survey. All other figures and relative category trends are close to those two studies.

2.4 Between Theory and Data

In all sociological studies, theoretical ambition collides with the quality of the dataset available. What are weaknesses of the dataset for describing responses to *anomie* during lockdown?

A first group of weaknesses come from the sample itself. The sample size is fairly small, too small for a really detailed examination of certain effects, in particular when these involve the interactions between numerous variables. For instance, while an effect can be shown linking being female and living with children to increased multitasking (section 5.2), once an attempt is made to take working from home into account, the size of the groups becomes simply too small to establish any credible effect, even though the raw data appears to show a very strong link. The same goes for any attempt to analyse the interaction of sex and class when looking at typical daily schedules (section 4).

Moreover, the low number of respondents in the 18-24 age category in the 2020 waves make the dataset unsuitable for examining this age group. Young people experienced very high levels of unemployment as those leaving education were unable to enter the job market (Brewer et al. 2020). Their specific experience of lockdown deserves a specially designed study; no attempt is made here to look at inequalities linked to age given the unreliability of any estimate for this age group. Among the other deficiencies in the sample, most important are the lack of ethnicity variable, and the very low number of those without qualifications, which must be kept in mind when examining the effect of educational level in section 6.

Secondly, the time diaries in this survey, as all time diary surveys, are not a perfect measure of time use. The framework of the questionnaire greatly influences the responses, as Chenu and Lesnard show with a neat comparison of two previous surveys (2006, 345-346). Certain aspects of this questionnaire are particularly notable. The number of activity codes is relatively small, which means that some codes, such as ‘Shopping, bank etc., including internet’ or ‘Telephone, text, email, letters’ are relatively ambiguous from the perspective of differentiating work from unpaid work and leisure. Moreover, as mentioned above (section 2.1) the click-and-drag entry method appears to have led to fewer activity periods per day. A paper questionnaire may accordingly have given a more detailed measure of time fragmentation. Finally, the 24-hour time period, though usual for a time-diary survey, is unfortunate in that any measure of 'routine' has to be based only on isolated days: a week-long diary would have been much more informative in this regard.

It is nevertheless worth underlining that time diaries similar to this one have been viewed as a 'gold standard', the best method currently available for recording time and far superior to questionnaires asking for a simple amount of time spent on each activity (Niemi 1993; Cornwell et al. 2019, 302). While the use of a digital method of data collection may have slightly changed the quality of the data, it allowed collecting data during lockdown when a traditional survey would have been far more difficult to carry out.

The most serious way in which the dataset determines any response to the research question is a more profound one, however, that comes from the very nature of time diary datasets. The act of filling out a time diary imposes on the day the very kind of division, planning and hierarchy of activities that is itself an object of the analysis. Javeau (1983, 75-76) criticises time diary surveys because they induce the respondent to reproduce the very ideal of measured, quantified, industrialised clock-on, clock-off time that is to be analysed and critiqued by a sociological study of time. Gershuny and Sullivan (1998) reply by arguing that the detail and methodology of modern time diaries allows them to be used to study forms of time use that do not conform to the 'industrial' paradigm critiqued by Javeau; I would agree, but only up to a point. Our capacity to do so remains limited by the medium. The day is always presented in terms of a sequence of activities with clearly defined boundaries, and any change in the extent to which the respondent may have seen it as such – a very relevant question in the *anomie* governing time use during lockdown – is inaccessible. Any attempt to measure a property not directly linked to activity sequences – such as, in this study, the extent to which the day was thought of as a planned sequence of activities – can only try to identify "shifts in time use budgeting that can be interpreted" as such phenomena (Rosa 2013, 129).

Moreover, in this study work can only be entered by the respondent as the single monolithic category of 'Paid Work, including at Home'. This excludes any study of the interior of this block of time, and in a sense removes it from the analysis. The experience of time at work, its subdivisions, attitudes to different parts of work, its intensity, are all *hors-question*. Time in paid work is implicitly assigned an undisputed value, and cannot be questioned or interrogated. The analysis therefore becomes not so much a study of work, as a study of the rest of life. Leisure activities can be examined and critiqued in their periodisation and quality (and are in this study). But no such questioning of paid work is possible: here the content of paid work is not something that the sociologist is allowed to analyse or question.

3 Method

Two main methods of analysis are used in this study: a classification of diary days, and linear regression models in order to estimate credible intervals for effects observed. These are outlined in this section, as well as the coding of certain variables that are used frequently throughout the study. Details of a variety of specific indicators that are used in only one section, such as the number of activity periods, or the times of waking up and sleeping up, will await the moment at which they appear. The whole analysis was carried out in the statistical language *R* (R Core Team, 2021); a code appendix is provided which allows recreating the entire analysis.

3.1 A Typology of Daily Routines

The dataset offers over 2500 vectors of primary activity codes. In order to meet one of the theoretical challenges posed in section 1, identifying common daily routines shared throughout society, a method is required to group similar vectors: ‘Optimal Matching’, the method which since the 1990s has become pre-eminent for this task in sociology. Optimal Matching has its origins in the analysis of genome sequences, and has since been applied not only to daily schedules but to social sequences of all kinds. (Reviews of its development can be found in Abbot 1995, Abbot and Tsay 2000, and Aisenbury and Fasang 2010.) In Optimal Matching, distances between sequences are estimated in terms of the minimum number of transformations required to turn one sequence into another. In contrast to other modelling methods that estimate an underlying state, such as event-history models, Optimal Matching looks at sequences without assumptions about what produced them. This has been a point of criticism (Aisenbury and Fasang 2010), but should in fact be seen as an advantage, especially in a period of social transition such as lockdown when previous assumptions about the causes of daily schedules may not hold.

The Optimal Matching of this dataset was based only on the primary activity vectors, which gave already very complex results without the addition of other vectors. (Future analysis might seek to take advantage of multi-channel Optimal Matching methods, although all other vectors had a very high amount of non-response which might adversely affect the findings.) It did not use the original 36 codes for primary activity, but conceptually grouped them into categories to ensure that activities with a similar social meaning were counted as equivalent. When determining the number of activity categories, it was kept in mind that Optimal Matching using more than a handful of categories produces fantastically complex results. Lesnard (2009, ch. 5) and Lesnard and Kan (2011) use only two categories, and no previous academic studies seem to use more than the eight of Vagni and Cornwell (2018). Here, the original activity codes were re-coded into five categories, following the division of As (1978) into necessary time, contracted time, committed time, and leisure time, as well as an 'other' category. These were interpreted as (Appendix B gives details of the grouping):

- **Rest**: sleeping, breaks, eating, washing, other self-care
- **Work**: Paid work, a single category in the original coding
- **Unpaid Work**: mainly housework, including childcare and DIY. Also included were care for dependent adults and associational work, although this last represents < 4% of unpaid work in the dataset.
- **Leisure**: a large variety of other activities, including socialising, hobbies, and exercise, though mostly made up by a single activity code that includes watching TV, videos and listening to music (see Figure 6.2.1 for details).
- **Other**: activities that were uncoded, written in, or explicitly given as 'other', but mostly categories representing travel, email and telephone, and shopping, which are ambiguous as to which of the preceding four categories the activity might properly belong.

Optimal Matching is in fact a family of related methods for estimating distance between sequences. All of them have in common the use of minimum numbers of transitions required to transform one sequence into another, but there are a large variety of methods which vary as to: the aspects of the sequence to be matched (activities, durations, transitions), the kinds of operations to be used (insertion, deletion, substitution), and the costs assigned to each operation. A recent overview is given by Studer and Ritschard (2016). Which method to use depends on the particular research question, since each takes different properties of a sequence into account.

The method used here is ‘dynamic Hamming distance’ (DHD), pioneered by Lesnard (2004, 2006 and 2010). The key insight behind this method is that when comparing 24-hour schedules to identify daily routines, what is of interest is not so much the sequence of activities as their *timing:* shared daily routines mean people doing the same activities at the same time. In order to identify which activities are done at the same time, it is only necessary to consider substitutions between spells, and not the possibility of inserting a new spell which would displace all subsequent ones. A second insight is that activity times that are socially more unusual should contribute to a greater difference between sequences, so that the final clustering reflects the relative social significance of differences in daily routine. The substitution cost between two events at a given time is therefore made inversely proportional to the amount of people who switch from the one to the other at that time (details can be found in Lesnard 2010). “With DHD the structure of the state space (distance between the states) is no longer static, but bends to the rhythm of collective life… The differences between states, which are variable over time, have a meaning for the agents in the given field. To work or not at 9:00 a.m. is not socially very significant, while the opposite would be true for 11:00 p.m” (Lesnard 2014, 48).

The main conceptual features that distinguish DHD from other Optimal Matching methods are that it is applicable only to sequences of equal length, and that it is very sensitive to changes in the exact timing of events (Aisenbury and Fasang 2010, 436-437). Studer and Ritschard’s (2019, 500) comparative analysis provides empirical support for this, showing that DHD is sensitive to differences in temporality rather than sequencing, and timing as opposed to duration. These features make it well adapted to the analysis of daily routine, where the sequences are all of 24-hour length and shifts to daily routine, defined in terms of changes in the precise timing of activities, such as stopping work at 6pm rather than 5pm, are the object of study. DHD is accordingly well adapted to the research question.

The implementation of DHD used was that of the *R* package *TraMineR* (Gabdinho et al. 2011). Weights were used in the calculation of substitution costs, as recommended by

Lesnard (2006, 13), so that the costs of transitions reflect behaviour in the population of reference, not just the dataset.

Once the distance matrix has been calculated, the final stage is to group similar sequences together. This requires a clustering algorithm. The analysis here follows Lesnard and Kan (2011) in using a method known as known as ‘beta-flexible UPGMA clustering’, developed by Belbin et al. (1992). This allows setting a constant ‘beta’ that controls how within-cluster distances contribute to the distance between new clusters. Lesnard and Kan (2011) use beta = -0.3. After experimenting with different clustering algorithms, and different values of beta for this algorithm, I agreed that their method seemed optimal, giving evenly sized clusters with understandable and interpretable patterns. The implementation of the algorithm used was the function *agnes()* from the *R* package *cluster* (Maechler et al. 2021).

The clustering algorithm requires a number of clusters to be set. Lesnard and Kan (2011) compare the clustering produced by setting many different numbers of clusters before selecting a number that seems the most appropriate. This study however innovates by not using simply the raw output of the clustering algorithm. Starting from a division into 24 clusters, which seemed an optimal value according to a comparison of cluster heights (cf. Lesnard 2006, 16), it was apparent that much detail concerning the scheduling of workdays, apparent in a division using a higher number of clusters, was lost. This first clustering was accordingly compared to a much more detailed version with 60 clusters, which was then regrouped by hand into a final set of 37 clusters, following the 24-cluster version while keeping certain clusters separate in order to preserve certain meaningful differences, particularly between workdays.

3.2 Models

Aside from the typology of daily schedules, most of the analysis involves demonstrating a link between factors such as class, education, sex, and survey wave on the one hand, and various aspects of time use such as amount of multitasking and number of leisure activities on the other. In all such cases, an effect in the survey sample is only evidence for an effect in the wider population, intervals for the probable size of which must be estimated. The method used in this study is regression modelling, using a Bayesian methodology that estimates credible intervals of posterior probability for parameter values given the observed data.

One key problem that is intrinsic to the composition of the dataset itself must be addressed. Because each respondent filled out multiple diaries, the diaries are not fully independent of each other. This is not ideal, because many statistical methods including linear regression on the whole assume that observations are independent. However, it was not possible to analyse the dataset in such a way as to ensure the independence of observations, since the dataset seems to be designed for by-diary analysis: the sample design and weighting provided is by-diary not by-respondent. Selecting only a single diary day per person would risk arbitrarily over selecting certain types of day (such as weekends), and more seriously would reduce the sample size, already small, by so much as to make the dataset unusable. For these reasons, all analysis in this study is by-diary, not by-respondent. While this will lead to somewhat over-optimistic estimation of credible intervals for parameter values, the dataset is nevertheless a unique opportunity to study the effects of lockdown, a situation in which data collection was far more difficult than usual and compromise to statistical ideals is unavoidable.

The regression models are linear, although there are very few continuous predictors: almost all the models only estimate intercepts for each category, so that the category intercept added to the population intercept is the mean of a distribution describing the outcome variable. The method is therefore analogous to estimating a difference in means, and on the same logic the important result is not each category intercept, but the *difference* in category intercepts, which is proportional (via the model's link function) to the difference in outcome. The advantage of linear models rather than a t-test is that the models allow including control variables as well as the multilevel pooling of categories.

This latter advantage is useful because much of the analysis is based on interactions of categories in order to estimate the differential impact of lockdown on social groups (e.g the intercept is estimated not for women overall, or August 2020 overall, but women in August 2020). which reduces the size of the groups and so decreases the confidence of the estimates. In order to mitigate this effect, the models (except for control variables) are fitted using a multilevel approach, simultaneously estimating the variance between categories as well as the intercepts for each category. This pools information across categories in order to reduce overfitting, making the model less 'sensationalist' by shrinking all intercepts towards the cross-category mean. It allows more reliable estimates to be obtained overall, and especially for categories that contain fewer observations, by making a weak assumption that each group will have a certain amount in common with others.

The choice of outcome distribution is important. Hammer (2012) discusses outcome distributions for modelling quantities of time in time diary data. The distribution of such quantities is often not Gaussian (normal); for instance he finds that when modelling childcare time, the best fit is given by a Gamma-Poisson distribution (also known as the 'negative binomial' distribution). Hammer notes that this makes conceptual sense, since a Poisson distribution models the count of an event that occurs with a rate, and a Gamma-Poisson distribution is a mixture of these, so the model can account for a mixture of housework tasks that recur with different rates. There is the additional factor that each event can have a different length, which when time is agglomerated will appear identical to a mixture of activities with different rates. In the present study, while the quantity of time is little examined in comparison to other aspects of time use, for the same reason the Gamma-Poisson distribution gives excellent fit to a wide variety of aspects of time use, and is most commonly used here. Other outcome distributions are occasionally used, sometimes justified conceptually, but other times simply by goodness of fit. Each is discussed at the moment used.

While use of weights is standard in calculating population means, using them in regression modelling, as in this study, has been more disputed. Two methods are available: a regression where observations are weighted with the survey weights, influencing their contribution to the estimation of parameters, or an unweighted regression where the variables on which the weights are based are included as independent variables (Winship and Radbill 1994). Weighted regression is *a priori* undesirable because it increases uncertainty in the parameter estimates. However, it is necessary when there is interaction between the variables on which the weight is based, as simply including them as controls can give biased estimates, unlike weighted regression which produces unbiased estimates in all cases (Young and Johnson 2010). This is the case here because the two variables corrected for by the weights, age and weekday, do interact, such as young people being more likely to work on weekends, and party on Friday night. The interaction may change over lockdown, since young people are more likely to work in sectors greatly affected by lockdown (Brewer et al. 2020, Henehan 2021). The interaction is sufficiently strong to affect some of the results in the study when unweighted regression was used. The regression models are accordingly weighted.

The linear regression models are fitted using Bayesian methodology, as implemented in the *R* package *brms* (Bürkner 2017) that is a front-end for the modelling language *Stan* (Carpenter et al. 2017). Customary uninformative 'flat' priors would have produced a very implausible distribution of outcome probabilities. Regularising priors were therefore used in order to reduce overfitting and help the computational model fitting process. Survey weights for the observations were incorporated using the *brms* formula component *weights()*, which influences the effect of each observation on the posterior distribution so that, for example, a weight of 2 as opposed to a weight of 1 is equivalent to including the observation twice in the model.[4] Each model was sampled in *Stan* over 3000 warmup and 6000 sampling iterations.

The model results are presented as posterior probability distributions, with credible intervals for the 'true' parameter values given the data, in order to aid visualisation of the uncertainty involved in the estimates. Bayes factors are also provided for the hypotheses that each parameter is above or below 0, in order to provide more intuitive interpretation of the probabilities involved. (The Bayes factor of $X > 0$ in this case is the ratio of the posterior probability of H1, $X > 0$, and H0, $X < 0$. So a Bayes factor of 10, for instance, indicates that, given the data and model assumptions, X is 10 times more likely to be above 0 than below 0, while a Bayes factor of 0.1 indicates the inverse.)[5] It is especially important to pay careful attention to the posterior probability estimates and Bayes factors, considering the actual probabilities involved rather than simply placing blind faith in 95%

4 https://discourse.mc-stan.org/t/weights-in-brm/4278 (accessed on 23/08/2020)
5 Computed using the function *hypothesis()* from *brms* (Burkner 2017).

intervals, given that the assumption of independence of observations is somewhat compromised, as outlined above. Andraszewicz et al. (2015) proposed the following widely referenced guide to interpretation of Bayes factors, which is used in this study.

Bayes Factor (BF)	**Interpretation**
> 100	Extreme evidence for H1
30 – 100	Very strong evidence for H1
10 – 30	Strong evidence for H1
3 – 10	Moderate evidence for H1
1 – 3	Anecdotal evidence for H1
1	No Evidence
0.33 – 1	Anecdotal evidence for H0
0.1 – 0.33	Moderate evidence for H0
0.033 – 0.1	Strong evidence for H0
0.01 – 0.033	Very strong evidence for H0
< 0.01	Extreme evidence for H0

3.3 Variables

Some predictor and outcome variables are used throughout the study, and for convenience their coding is described here. Other, used only once, are described at the moment they are used. The dataset variables ‘econstat’ and ‘dagegrp’ were used to define age and student status for the purposes of defining the sample. The relevant survey questions are given in Appendix A.

Survey Wave: variable ‘survey’. The wave of survey in which the response was collected, ‘2016’, ‘June 2020’, or ‘August 2020’.

Sex: variable ‘sex’. ‘Male’ or ‘Female’.

Class: variable ‘dclasuk’. 3-class NS-SEC classification, as defined by the ONS,[6] including two additional categories for students (who are excluded here) and other inactive people. Categories: ‘Higher managerial, administrative and professional occupations’, ‘Intermediate occupations’,‘Routine and manual occupations’, ‘Not working, never worked and long-term unemployed’. This was preferred to Social Grade, the occupational

6 https://www.ons.gov.uk/methodology/classificationsandstandards/otherclassifications/thenationalstatisticssocioeconomicclassificationnssecrebasedonsoc2010

scale defined by the National Readership Survey and widely used in marketing research, since it is more modern and incorporates not only occupation but also self-employment, size of organisation and supervisory position. It is conceptually based on the Goldthorpe schema (Goldthorpe 1980).

Age: variable ‘dagegrp’. 5 categories: ‘18-24’, ‘25-34’, ‘35-44’, ‘45-54’, ‘55-64’. Values of ‘65+’ excluded from the sample (see section 2.1). Used as a control only.

Degree: recoded from variable ‘hied’. The highest qualification the respondent has received. Available options were Higher Degree, First Degree, A-Levels, Apprenticeship, GCSE, No qualifications. In the analysis these are grouped into ‘Degree’ and ‘No Degree’.

Has Children: recoded from variables ‘nunder5’, ‘n5to11’, ‘n11to16’. ‘Children’ if answered more than 0 to any category in a question asking how many children are in the household (with a maximum age of 16), ‘No Children’ otherwise.

- **Employment Status in Lockdown**: recoded from variable ‘emplnow’. Survey waves in 2020 only. Employment status during lockdown; many options given (see Appendix A), recoded into ‘full time’, ‘part time’, ‘furlough’, ‘not working’.
- **Working**: recoded from ‘econstat’, combined with Survey and Employment Status in Lockdown. Extends Employment Status in Lockdown to cover the 2016 wave.
    - If **Survey** is ‘2016’:
        - If ‘econstat’ is in set [1-4] (see Appendix A), then ‘Working’
        - Otherwise, ‘Not Working’
    - If **Survey** is ‘June 2020’ or ‘August 2020’:
        - If **Employment Status in Lockdown** is ‘Full time’ or ‘Part Time’, then ‘Working’,
        - Otherwise, ‘Not Working’.

Cluster: 37 categories: the cluster defined by the Optimal Matching analysis (see section 3.1, and the Code Appendix).

Workday: 'Workday' if the cluster of diary day is in the set [1-15, 36], (that is, days with significant amount of paid work), 'Not Workday' otherwise.

9 to 5 Workday: '9 to 5 Workday' if the cluster of diary day is in the set [4-11], 'Other Workday' if the cluster of diary day is in the set [1-3, 12-15, 36], NA otherwise.

Day Type: A per-day, rather than per-person variable. A measure of work from home was created by calculating the proportion of primary activity 'Paid Work' that was also coded as 'Home' (as opposed to 'Work' or 'Outside') on the location diary vector. Then combined with **Workday** and **In Work:**

- If **Workday** is 'Workday', then if more than 50% of of 'Paid Work' time is at home, then 'Home Workday', else 'Outside Workday'. (50% is not an important figure, since only ~5% of diary days had a proportion between 5% and 95%).
- If **Workday** is 'Not Workday':
    - if **In Work** is 'Working', then 'Not Workday, Working'
    - if **In Work** is 'Not Working', then 'Not Workday, Not Working'.

Mental Health: A mental health assessment questionnaire was included in the 2020 waves of the survey (although it was not asked to the first 329 diaries in June 2020). This asked respondents to subjectively assess whether their mental state had changed since the beginning of lockdown in twelve different ways. It is a subjective measure of the impact of lockdown on mental health, rather than an objective one, although that is somewhat mitigated by some of the questions asking in terms not obviously relating to mental health, such as 'playing a useful part' or 'able to make decisions' (see Appendix A). An objective measure would be desirable, but this is used as the best available here.

Only eleven of the twelve questions were used, since question 5 had an inordinately high number of non responses that appear to be due to the survey processing. Four options were available: 1 = 'Less so than usual' (which implies better mental health), 2 = 'Same as usual', 3 = 'More so than usual', and 4 = 'Much more than usual'. The questions have consistent responses, and Cronbach's alpha for the responses to the eleven questions used, calculating using the numeric values from 1 to 4, is 0.89. The 11 responses were combined into a single index by subtracting one from each numeric value and then taking the average, creating a continuous scale from 0 to 3, where 0 reflects improved mental health, 1 no change, and 3 worse mental health.

4 Structuring Daily Routine

The first way of analysing responses to *anomie* of time use during lockdown in this study is daily routine. As discussed above (section 1), daily routine is a marker of social class, a comforting reference point for common sense, and may be the result of scheduling activities to ensure their organisation and productivity. The preservation – or not – of daily routine can be seen as a way of continuing 'normal life' in the *anomie* of lockdown by applying norms of activity timing relevant to the pre-lockdown social situation. Furthermore, this response is not only the result of choices as to how to spend the 'free time' created by lockdown, but will also be marked by male-female and class inequalities resulting from shifting obligations of work schedule as well as housework and childcare.

The study of daily schedules in their entirety, as opposed to simply quantifying the amount of time spent in particular activities, is a relatively recent trend in time-use study. A review of the English literature on the subject is given by Cornwell et al. (2019, 311-312), and the French by Chenu and Lesnard (2006, 349-354). Most work has focused on work schedules (e.g. Lesnard 2009, Lesnard and Kan 2011), but Vagni and Cornwell (2018) extend their analysis to non-work days, something that I pursue here in a much more detailed typology.

While the dataset is not longitudinal, individual daily schedules can be compared in order to identify common patterns of activity, routines shared across society. The synchronisation of collective activities is a feature of society: the agricultural calendar, the week structured by the religious service and bells ringing out across a the medieval city, the modern rush hour (Lesnard 2014). This is not only a property of collective activities but extends to the mass of individual daily schedules, which are all more or less in synchronicity with each other. Daily activities are organised into a routine, in which the activities are in mutual relation as part of an organised whole. While daily routine might seem something very individual, the fact that each person's routine is more or less in sync with others' – which Lefebvre's rhythm-analysis (1992) would term *isorhythmia* – gives a social meaning to each activity and its timing. For instance, working a night shift, going for a morning run, leaving work in time to pick up a child from school, are all activities which get a social meaning from the fact that they are done at the same time as a particular set of other people in society.

The results therefore concern daily routine in the structuring of a single day, rather than implying the consistency of that routine over multiple days. The latter could be inferred, nevertheless, on the assumption that if many different people from the same social group structure their days in the same way, then one person from that group will structure many of their days in a similar way.

The grouping of daily routines divides the 2 583 diary days into 37 clusters. The method used here is a statistical algorithm, a form of Optimal Matching, but the final grouping involved manual intervention to ensure clusters that were not only mathematically justified but sociologically meaningful (details are given in section 3.1). The purpose of the analysis is to distinguish changes in daily routine in terms of the timing and fragmentation of work, unpaid work, leisure and rest or self-care activity periods, and so the final choice of 37 is justified not only on mathematical grounds, but by the meaningfulness of the differences between each cluster in this regard. The clustering is far more detailed than that of previous research (cf. Vagni and Cornwell 2018), allowing a more detailed appreciation of patterns; the clusters can then be regrouped into large categories for statistical modelling.

The preservation (and non-preservation) of daily routine will become apparent during lockdown, in its continuity, change, and sometimes complete collapse. The analysis proceeds in 5 sections, according to the dominant form of activity: Workdays, Unpaid 'Workdays' (dominated by housework), Leisure days, 'Disrupted days' in which waking and sleeping times are widely shifted from the usual, and 'Other'. Finally, the link between daily routine and mental health in lockdown will be examined.

Before the detailed analysis, all the clusters are shown in Figure 4.1, with some indicative summary statistics provided in Table 4.1. The cluster numbering indicates adjacency in the output of the clustering algorithm, so that 1 and 2 are evaluated as more similar than 1 and 10, for example. (It is not however the case that all adjacent numbers are similar, since the clustering is in the form of a tree, so that some adjacent numbers have only a distant common ancestor.) They are each shown in Figure 4.1 with the graphic sometimes known as a ‘tempogram’, where the percentage of people in the group doing a given activity is plotted throughout the day from 4am to 4pm, with a description of the routine shown. Vertical lines at 9am, 5pm (solid) and 12pm (dashed) are given to aid reading.

Taking cluster 4 as an example, starting from the left at 4am everyone out of the 184 respondents is sleeping. Between roughly 7am and 9:30am, they all wake up and quickly start work, some with brief periods of leisure, unpaid work or ‘other’ activity first. They then all work continuously throughout the day until 5pm; and between 12pm and 2pm around 10-25% of them are on a lunch break (coded as rest). In the evening there are periods of ‘other activity’ (such as a commute) as well as rest/eating time for around 10-30% at any one time, as well as a few who do housework, hen from 7pm onwards almost all engage in leisure activities, and literally cluster members for a moment around 9-10pm, before everyone is in bed by midnight.

Another important aspect of the representation is when multiple different activities are done at the same time by members of the same cluster: for example, between 9am and 12pm in cluster 13. This does *not* on the whole indicate that some members of the cluster did unpaid work for the entirety of this time, others leisure, etc. If so, the Optimal Matching process would have separated them. Instead, it indicates that during these time periods, each respondent engaged in short periods of alternate work, leisure etc., and that respondents’ time was fragmented between these activities. In this example, each respondent spent on average ¼ of the time doing unpaid work, but people did it at different times.

This within-cluster synchronicity can be measured in terms of entropy, specifically the average between-diary entropy across slots. The precise measure used here is that of Lesnard (2010, 404-405, though for a different purpose than that study): If p_{tj} is the proportion of respondents who do activity j (out of q total activities) at time t, then entropy at time t can be defined as:

$$H_t = -\sum_{j=1}^{q} p_{tj} \ln(p_{tj})$$

It is bounded by 0, when all individuals are in the same state, and *ln(q)*, when all individuals are in different states. This is then averaged over all time slots in the cluster. Here it is calculated on the bases of the five activity groups used in the clustering, giving a maximum value of *ln(5)* = 1.6 (the results below, however, are little changed if it is calculated on the bases of the original activity coding instead). The average entropy over slots, as a percentage of the maximum possible entropy, is provided in Table 4.1, and is used in the analysis in section 5.2. In a sense, it is a measure of the extent to which the routines in the cluster are in-sync with any others in society.

Table 4.1

Cluster	% Female	% With Children	% Not Working	% Degree	% Higher Professional	% Intermediate	% Routine	Modal Age Group	Mean Entropy As % Of Max Entropy
1: Workday Morning, short	68.1	26.0	3.4	48.1	38.7	27.7	30.2	55-64	44.8
2: Workday 9 to 5, early start	45.4	35.4	2.2	59.1	31.9	39.6	28.4	35-44	36.8
3: Workday Morning, long	42.8	44.9	2.8	28.1	20.4	24.0	52.8	45-54	39.1
4: Workday 9 to 5	41.2	37.2	2.6	61.6	57.7	19.0	22.1	45-54	26.4
5: Workday 9 to 5, more leisure	28.4	37.8	1.6	49.5	45.6	34.4	19.4	45-54	25.9
6: Workday 9 to 5, unpaid evening	48.1	36.6	0.9	61.1	53.4	29.9	16.8	45-54	32.9
7: Workday 9 to 5, other evening	48.8	37.4	6.5	72.9	65.7	23.3	11.0	35-44	41.2
8: Workday 9 to 5, long	32.9	33.5	0.0	51.8	58.7	18.7	22.6	45-54	31.6
9: Workday 9 to 5, no leisure	41.0	47.7	1.2	64.5	57.8	32.5	8.5	25-34	27.2
10: Workday 9 to 5, long leisure	28.1	58.3	2.0	59.1	42.7	15.0	40.3	25-34	36.1
11: Workday 9 to 5, night leisure	35.5	57.6	12.4	53.5	50.2	11.5	33.6	35-44	38.4
12: Workday Afternoon	25.2	33.9	7.1	72.7	54.2	28.1	14.0	25-34	41.7
13: Workday Afternoon, short with unpaid	52.5	39.6	23.1	65.3	40.4	34.4	21.1	35-44	44.2
14: Workday Afternoon, short	33.6	49.9	7.4	79.4	15.2	35.5	30.9	55-64	37.3
15: Workday Afternoon, long	71.3	45.0	0.0	50.7	54.6	3.7	41.6	25-34	25.3
16: Unpaid and Leisure, morning unpaid	59.7	46.5	36.8	51.5	41.5	20.8	22.2	55-64	42.7
17: Leisure, interrupted	55.6	30.2	45.4	56.8	29.2	24.8	23.5	55-64	51.0
18: Unpaid and Leisure, unpaid afternoon	55.5	38.9	52.5	58.0	41.1	25.6	18.6	55-64	43.4
19: Disrupted Day, short	64.5	38.0	32.4	66.3	39.4	20.3	24.8	35-44	47.2
20: Disrupted Day, mixed	54.7	49.8	26.9	55.5	30.3	14.8	37.7	45-54	72.3
21: Unpaid Workday, long	66.4	80.2	50.9	47.6	27.5	23.2	19.1	25-34	30.7
22: Unpaid Workday, lunch	65.8	62.9	29.2	58.6	51.3	21.0	12.4	55-64	49.1
23: Unpaid Workday	49.8	36.9	44.1	57.3	36.1	23.2	21.0	55-64	31.1
24: Other and Leisure, other afternoon	60.2	25.1	46.9	59.8	27.8	25.9	14.2	55-64	50.7
25: Other and Leisure, other morning	62.0	32.1	38.8	43.5	41.7	16.0	16.9	45-54	46.6
26: Disrupted Day, short leisure evening	47.1	44.5	27.1	52.0	46.4	21.0	23.6	45-54	43.2
27: Rest, interrupted	46.8	33.5	51.5	45.6	24.6	14.1	23.9	55-64	22.5
28: Leisure, all day, late start	35.8	13.5	59.2	29.2	43.8	15.2	17.6	55-64	26.7
29: Leisure, slightly interrupted, late start	48.6	24.5	37.5	55.0	35.2	18.8	30.9	55-64	32.9
30: Leisure, interrupted, late start	60.2	24.7	43.1	60.4	44.7	17.0	21.9	55-64	47.5
31: Other and Leisure, other morning, late start	45.0	25.5	37.2	36.2	35.1	18.4	27.8	55-64	39.9
32: Unpaid and Leisure, morning unpaid, late start	64.0	33.2	49.7	52.1	39.6	24.3	18.1	55-64	42.7
33: Leisure, all day	38.5	26.8	30.5	40.4	31.3	22.8	33.2	45-54	26.5
34: Disrupted Day, long leisure evening	55.1	19.5	49.8	53.8	30.8	16.1	20.3	55-64	51.1
35: Disrupted Day, overnight	25.8	55.9	16.3	59.9	56.5	14.2	15.7	35-44	69.6
36: Workday, night shift	57.7	47.4	0.0	41.6	38.9	19.7	41.4	45-54	58.2
37: Rest, all day	14.1	59.2	29.5	27.4	27.8	11.6	34.6	45-54	0.0

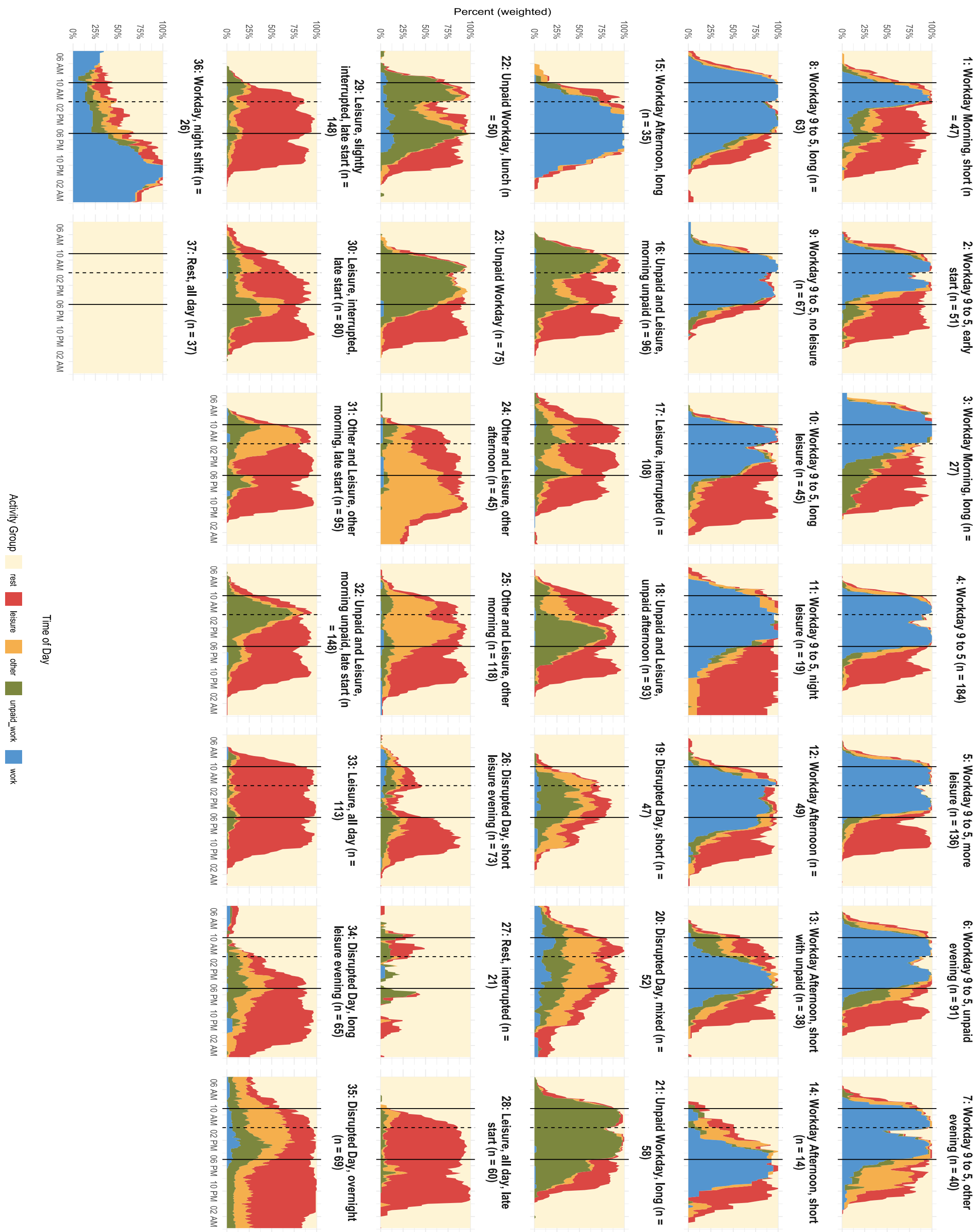
1: Workday Morning, short (n = 47)
2: Workday 9 to 5, early start (n = 51)
3: Workday Morning, long (n = 27)
4: Workday 9 to 5 (n = 184)
5: Workday 9 to 5, more leisure (n = 136)
6: Workday 9 to 5, unpaid evening (n = 91)
7: Workday 9 to 5, other evening (n = 40)
8: Workday 9 to 5, long (n = 63)
9: Workday 9 to 5, no leisure (n = 67)
10: Workday 9 to 5, long leisure (n = 45)
11: Workday 9 to 5, night leisure (n = 19)
12: Workday Afternoon (n = 49)
13: Workday Afternoon, short with unpaid (n = 38)
14: Workday Afternoon, short (n = 14)
15: Workday Afternoon, long (n = 35)
16: Unpaid and Leisure, morning unpaid (n = 96)
17: Leisure, interrupted (n = 108)
18: Unpaid and Leisure, unpaid afternoon (n = 93)
19: Disrupted Day, short (n = 47)
20: Disrupted Day, mixed (n = 52)
21: Unpaid Workday, long (n = 58)
22: Unpaid Workday, lunch (n = 50)
23: Unpaid Workday (n = 75)
24: Other and Leisure, other afternoon (n = 45)
25: Other and Leisure, other morning (n = 118)
26: Disrupted Day, short leisure evening (n = 73)
27: Rest, interrupted (n = 21)
28: Leisure, all day, late start (n = 60)
29: Leisure, slightly interrupted, late start (n = 148)
30: Leisure, interrupted, late start (n = 80)
31: Other and Leisure, other morning, late start (n = 95)
32: Unpaid and Leisure, morning unpaid, late start (n = 148)
33: Leisure, all day (n = 113)
34: Disrupted Day, long leisure evening (n = 65)
35: Disrupted Day, overnight (n = 69)
36: Workday, night shift (n = 26)
37: Rest, all day (n = 37)
Percent (weighted)
0%
25%
50%
75%
100%
Time of Day
06 AM
10 AM
02 PM
06 PM
10 PM
02 AM
Activity Group
rest
leisure
other
unpaid_work
work

Figure 4.1

4.1 Workdays

Figure 4.1.1 shows 16 diary day clusters, each the pattern of a typical workday in the dataset. Many of the 16 typical workdays, nos. 4-11, have a period of work extending at

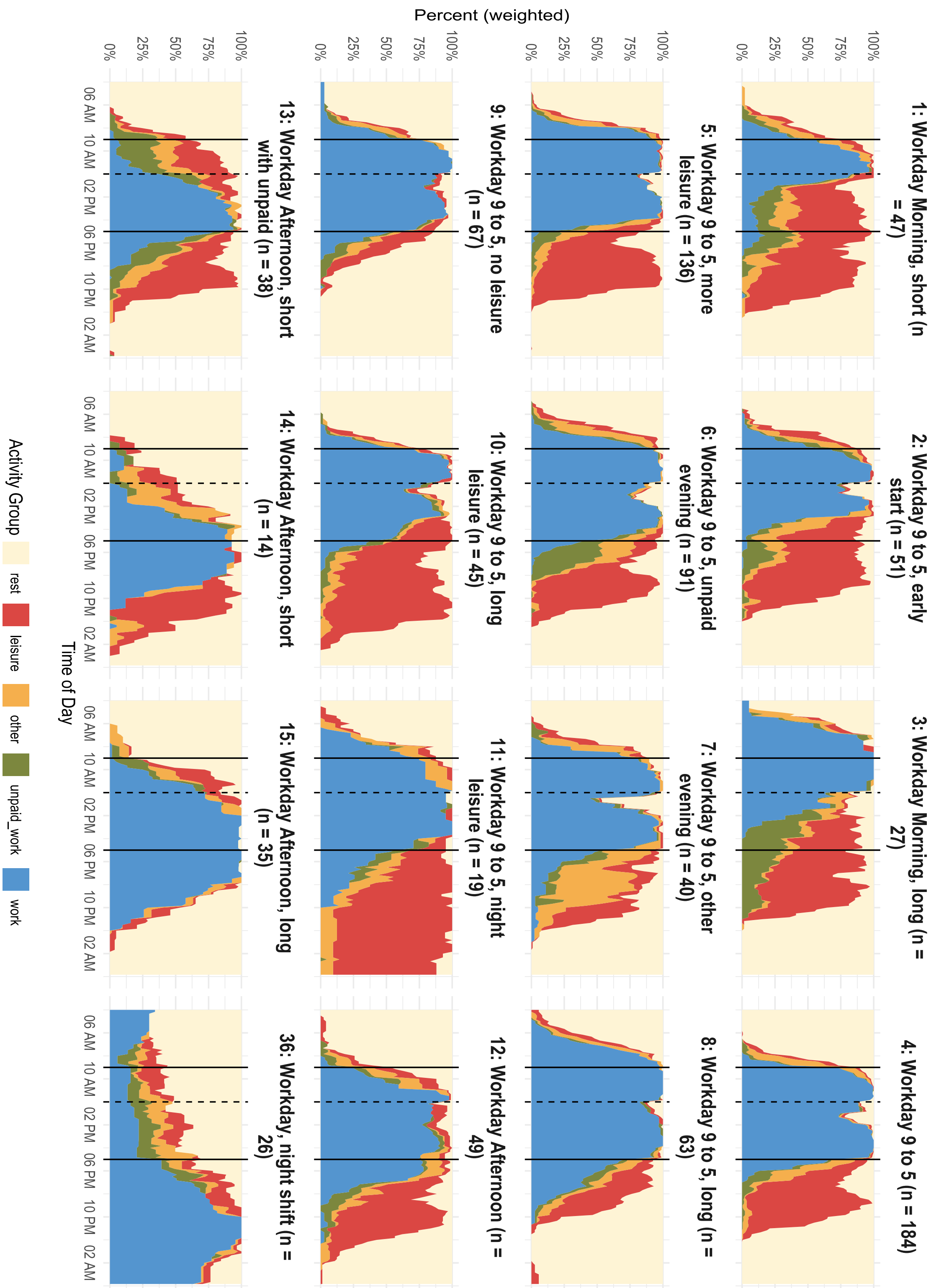

Figure 4.1.1: Workday Clusters

least from the traditional hours of 9am to 5pm, with a single lunch break. These are classed here as '9 to 5' workdays, although many of the work hours overflow these bounds. They are by far the most common kind of workday in the dataset, and are the workday conventionally associated with a regular job. There are nevertheless differences between them; cluster 4 is the closest to 9 to 5 working hours, cluster 5 starts a little earlier, includes more leisure time, and has a more clearly defined dinner time. Some clusters such as 8 and 9 have very little leisure, and in cluster 8 the workday completely overflows the 9 to 5 boundaries. Cluster 6 shows the 'second shift' of those who come back from work to do housework.

The other clusters mostly imply shift work (cf. the similar classification of Lesnard and Kan 2011); Clusters 1 and 3 start and finish early, as well as 2 which nevertheless has the appearance of an early-shifted 9 to 5 workday. Clusters 12-15 start late and end late, which sometimes indicates an afternoon shift but as shown below (Figure 4.1.4) is also a typical pattern when working from home. Cluster 36 is a group for all those with working hours who do not fit into the above (such as night shifts); the disruption to sleep pattern is such that the clustering algorithm associates it not with workdays but other highly disrupted days (such as clusters 34 and 35 in section 4.4 below).

Figure 4.1.2 shows the proportion of *all* diary days in each survey wave (workdays and non-workdays) that belong to a given cluster, looking for the moment only at workdays. Note the variable y-axis: 9 to 5 workdays are about 4 times more common than other workdays. The picture is complex, but certain patterns emerge. The most common workdays in 2016 were clusters 4-6, the '9 to 5' workdays whose working hours are closest to '9 to 5', and these accordingly represent most of the decline in workdays in June 2020 compared to 2016, and rebound as restrictions are relaxed in August 2020. The other days that decreased most in lockdown compared to 2016 are morning shift work, clusters 1-3, perhaps a reflection of workers in sectors dominated by such work (construction, tourism) being more likely to stop work (Brewer et al. 2020). Afternoon shifts (clusters 12-14) on the other hand become more common in June 2020, and decrease again in August 2020. As shown below in Figure 4.1.5, this seems to be because they are typical patterns in working from home during the first lockdown; they decrease in August (although working from home does not decrease, cf. Figure 4.1.7 below) as workers from home transition back to more conventional work schedules. Meanwhile, clusters 8, 9 and 15 – long workdays, with little or no leisure time but only rest and work – increase through lockdown in June 2020 and continue to increase into August 2020. The ‘second shift’, cluster 6, appears to decrease in lockdown (though the number of cases is too small to be confident of this effect), perhaps explained by the opening up of other times in which housework is possible.

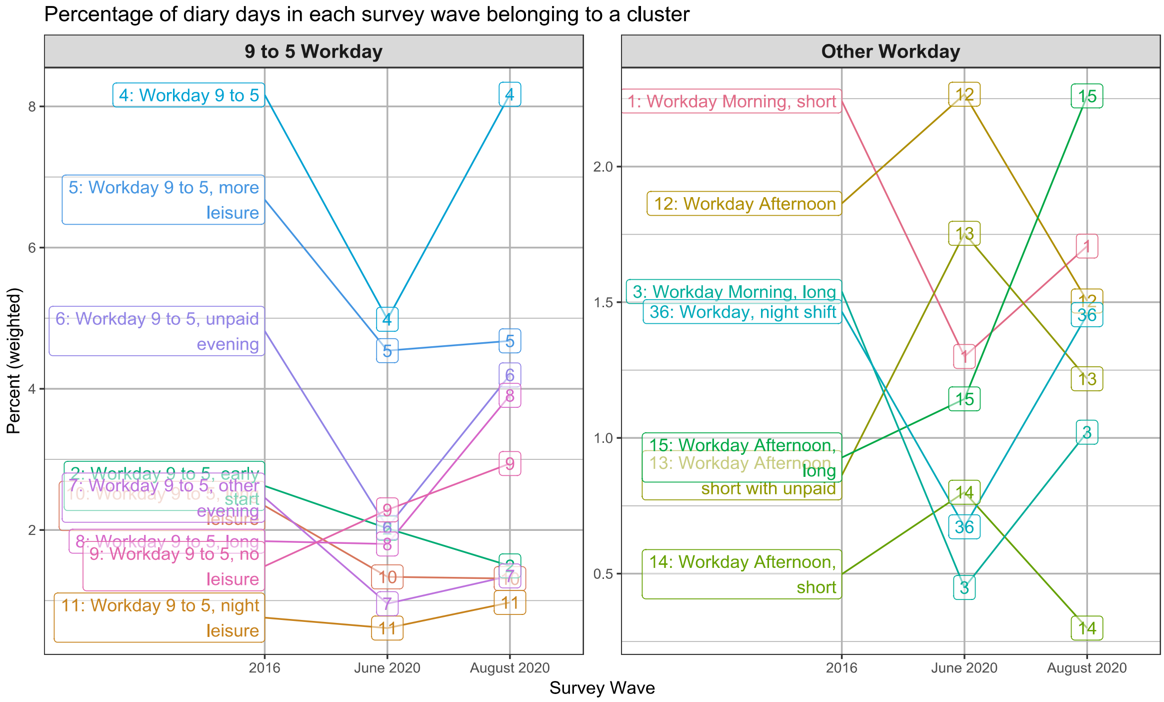

Figure 4.1.2

Model 4.1.1 fits a linear regression model to estimate credible intervals for the size of these effects, grouping typical workdays as in the previous paragraph (with clusters 8 and 9 excluded from the group of 9-5 workdays). The groups of typical workdays are categorical outcomes in a softmax model where survey wave is the predictor, and the pivot (reference) category is ‘any other workday’. Controls were not included, since the survey design is representative across survey waves on a wide variety of indicators (see sections 2.1 and 2.2). Unlike Figure 4.1.2, the model excludes the effect of stopping work, by estimating the change as a percentage of workdays (n = 932) rather than a percentage of all days, so that the coefficients are relevant to what is the ‘typical workday’ in each survey wave. As outlined above (section 3.2) the relevant values are the difference in linear model intercepts, such as 'June 2020 – 2016' where a positive value indicates that a group of clusters is more common in June 2020 compared to 2016, and the posterior probability distribution of this difference calculated, from which credible intervals for the actual size of the difference, given the data, are shown in Figure 4.1.3 (full results are given in Appendix C).

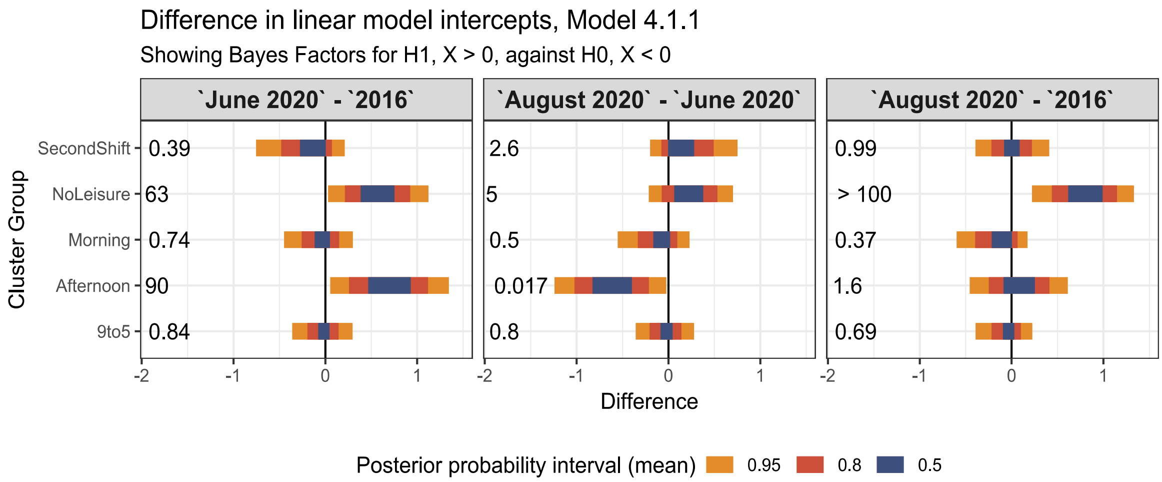

Figure 4.1.3

Cluster 6, the 'second shift', is somewhat more likely to have decreased into June 2020 and increased into August than the opposite, but the effect is no credible at95%. (The Bayes factors indicating moderate evidence each time, firstly that a negative change is about 2.5 (≈ *1 / 0.39*) times more likely than a positive change between June and 2020, and then that a positive change is 2.6 times more likely than a negative change from June to August; cf. Section 2.3.) Morning shift workdays and 9 to 5 workdays do not change as a proportion of all workdays, and any shift in their amount is a result of overall increases and decreases in the total number of workdays. The most important effects, credible at 95% and with Bayes Factors indicating a strong degree of evidence, are firstly the long workdays without leisure time (clusters 8, 9 and 15 taken together), which become more prevalent in June 2020 compared to 2016, and perhaps slightly more so into August 2020, for a strong overall change (the right panel). These days are evidence for intense overwork and a displacement of leisure by 'rest' (meals, naps and sleep). Secondly, afternoon workdays (clusters 12-14 taken together) increase in June 2020 compared to 2016, and decrease again into August, implying that this late start to work is a lockdown-specific work pattern.

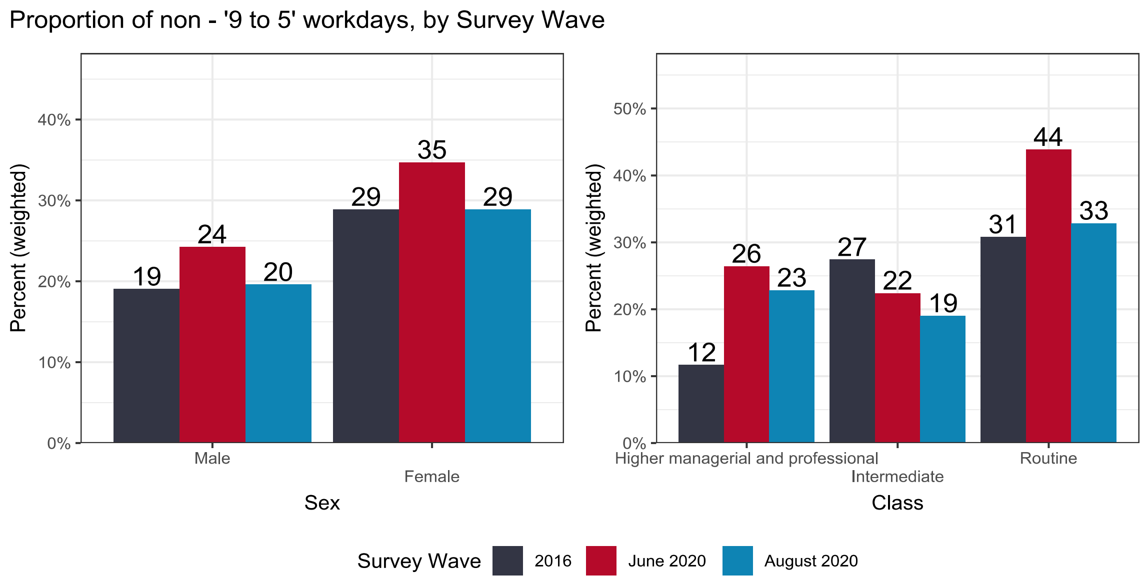

Figure 4.1.4

While Model 4.1.1 found no evidence for an overall increase or decrease in 'standard, '9 to 5' workdays as a proportion of all workdays, when male-female and class differences are taken into account, some patterns emerge. Figure 4.1.4 shows the proportion of workdays that are 'non-standard', defined as workdays not in clusters labelled as '9 to 5' in Figure 4.1.1. Considering the difference between men and women, there is maintenance of the pre-lockdown inequality whereby women are more likely to have non-standard work hours – a pattern known from previous research (e.g Jacobs and Gerson 2004). The pattern when considered by social class is different (see section 3.3 and Appendix A for an explanation of the three-class grouping used in the analysis). It would appear that those in 'Higher managerial and professional' occupations increased the proportion of non-standard workdays over survey waves, 'Intermediate' occupations decreased, and 'Routine' occupations increased only in June 2020, but not in August 2020.

Model 4.1.2 predicts the probability that a workday is a non-standard workday (that is, not '9 to 5', defined by the subjectively assigned cluster labels in Figure 4.1.1) by class group and survey wave, controlling for age and sex, using a logistic regression. The results in terms of the difference between classes are shown in Figure 4.1.5 (full results are in

Appendix C), so that a positive coefficient corresponds to a higher probability of a non-standard workday. There is strong evidence for a difference in the rates of non-standard workdays between 'Higher managerial and professional' occupations and the other two class groups in 2016. This reproduces a result for the well-known class inequality in this regard (e.g Chenu and Robinson 2002, Jacobs and Gerson 2004). However, in the 2020 survey waves, the evidence for this difference is much weaker, and the difference comes principally between 'Intermediate' and 'Routine' rather than between 'Higher' and 'Intermediate'.

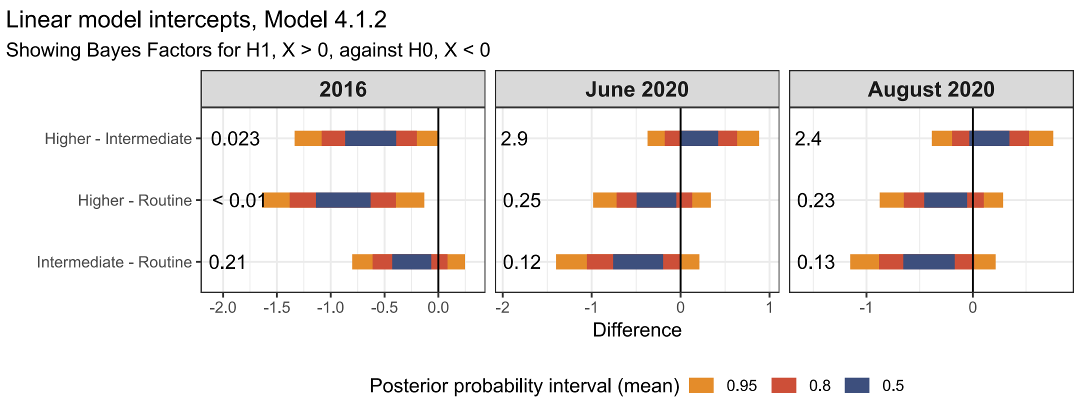

Figure 4.1.5

Figure 4.1.6 shows the results of Model 4.1.2 once more, this time in terms of the difference between survey waves. It reveals that the only class group for which there is strong evidence for a change in the proportion of non-standard workdays is Higher managerial and professional occupations, for whom there is very strong evidence of an increase in June 2020 compared to 2016, a change which is maintained into August 2020. It is this group that is contributing to the apparent shrinking of the class based inequality in non-standard schedules; once controls are included, there is little evidence for the other changes over survey waves shown in the right panel of Figure 4.1.4 above.

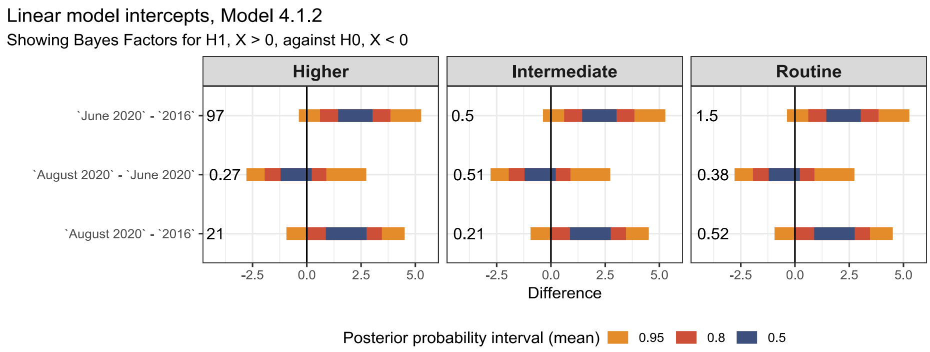

Figure 4.1.6

The shift to working from home is generally considered the most important change in workdays during lockdown. Figure 4.1.7 shows how that is reflected in the dataset: working from home rose both as a proportion of workdays and absolutely into June 2020, and continued to rise while declining as a proportion into August 2020. Model 4.1.3 evaluates the association of each typical workday with working from home (details of how ‘working from home’ is assessed are in section 3.3). The model is a logistic regression, with cluster (interacting with survey) as a predictor and working from home coded as 1, not working from home as 0 (Full details are in Appendix C). No controls were included, in order to estimate only the relationship between working from home and daily routine. The results are shown in Figure 4.1.8.

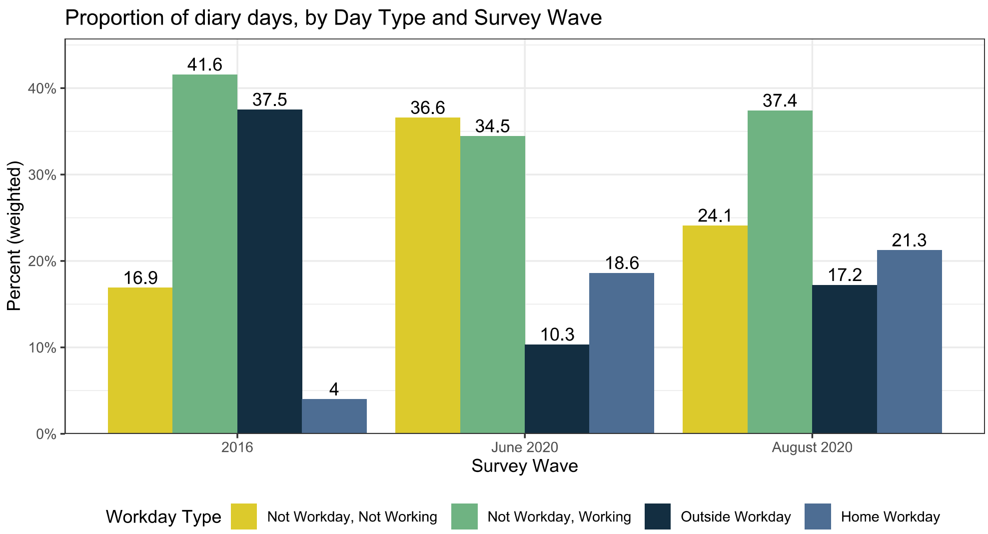

Figure 4.1.7

In 2016, when relatively few worked from home, almost all kinds of workdays, unsurprisingly, involve working from home than the average across all three waves. However, in June 2020, working from home becomes generalised, and all forms of workday become at least as likely as not to involve teleworking, compared to the cross-category average (with the probable exception of cluster 3). Moreover, some workdays became positively associated with working from home. A first group are clusters that in the context of work outside the home would imply shift work: 1, 13 and 14 (along with the similar 12 and 15, though these not individually at 95%). Cluster 14, a short afternoon workday, appears to be particularly favoured and seems to imply an ideal work schedule of someone with enough control of their work schedule to work only a short day. The second group are certain forms of 9 to 5 workday, clusters 4, 6 and 7.

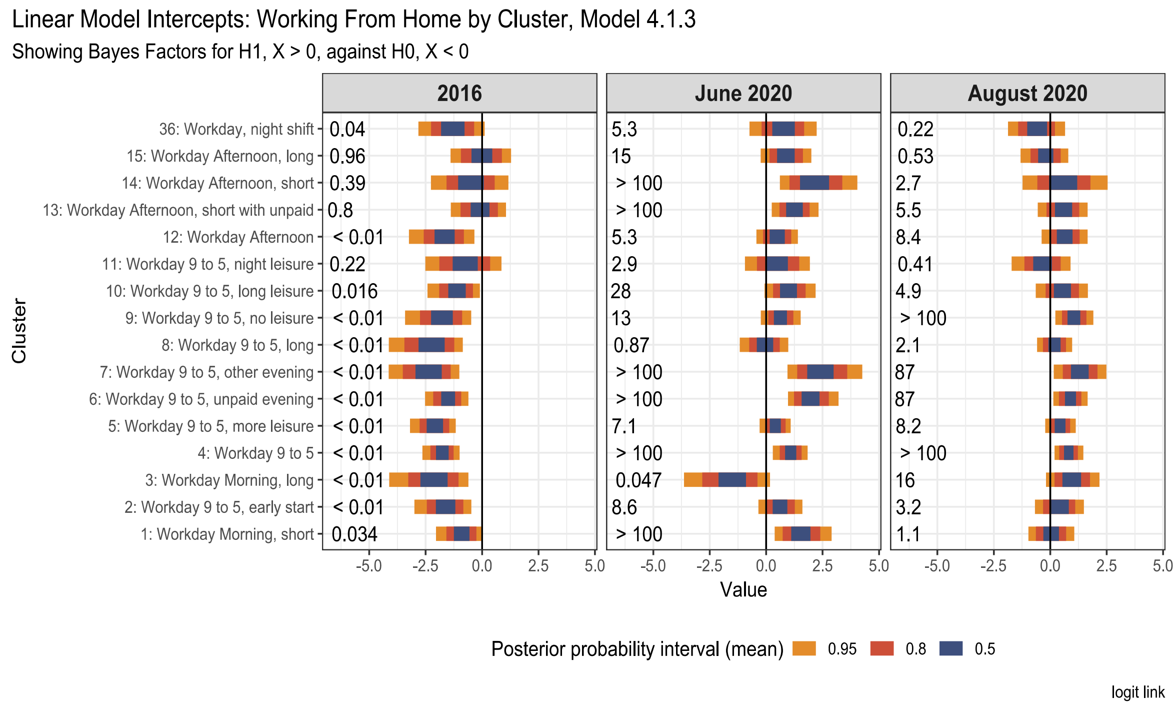

Figure 4.1.8

In August 2020, working from home is no longer characterised by certain workdays and patterns have become generalised to all forms of workday. Days working from home no longer look like shift work (1, 13, 14) and the only workdays that retain a positive association with strong evidence, and credible at 95%, are 4, 6, 7 and 9, relatively regular and standard 9 to 5 workdays. It seems that in June 2020 people responded to working at home partly by assuming an afternoon work pattern that had been unusual in 2016, and partly by transposing their previous workday pattern into new circumstances. But as working from home became more normalised into August, people re-established pre-lockdown routines, and discarding the late starts and early finishes implied by clusters 1, 13 and 14.

Overall, lockdown made little difference to relative rates of standard 9 to 5 workdays and morning shift work, which declined at a similar rate to the overall decline in days worked. It did, however, cause an increase, firstly in long workdays without leisure, an increase which lasted into August 2020, and secondly in workdays resembling an afternoon shift, which did not. The latter, although not the former, is linked to working from home. There is also a specific link between higher qualified occupations and non-standard work schedules in the 2020 waves, which may be related to the increase in working from home (in June 2020; the effect however persists into August 2020, and the it is not possible with the size of dataset available to determine if this is indeed the cause).

I would suggest that these results show a remarkable persistence of the 9 to 5 workday, which may be due either to employers' control over work hours or workers' desire to maintain routine. While some workers took advantage of working from home to shift to an afternoon-centred workday, this appears to have been rejected in the longer term in favour of a return to the 9 to 5 workday, especially among less qualified workers. Higher qualified workers, meanwhile, found themselves more often in non-standard work schedules, which decreased the pre-lockdown inequality in this regard. A final result is that overwork at the expense of leisure does become more common; the cluster that most epitomises this tendency, cluster 8, becomes one of the most common forms of workday in August 2020 (Figure 4.1.2).

4.2 Unpaid 'Workdays'

The six typical days shown in Figure 4.2.1 are the clusters typified by a large amount of unpaid work, a category mostly made up of childcare and other housework, with some DIY (see section 3.1 with Appendix B). Since by definition they are not paid workdays, the rest of the day is mostly taken up with leisure, while the 'other' category includes activities such as emails and shopping that although ambiguous could also represent unpaid work. Clusters 21-23 resemble workdays (such as clusters 8, 7, and 12 in Figure 4.1.1), where paid work is replaced by unpaid work. A proportion of the diary days in these clusters (as much as 30% in cluster 22) are sufficiently structured to include a clear lunch break. The other three clusters combine unpaid work with leisure, with the unpaid work concentrated in a specific period of the day: in cluster 32 this is the late morning/midday, 18 the afternoon, and 16 the earlier morning with many recommencing in the afternoon. I would suggest that this reflects an amount of planning or structure to the day, even at a simple level; for instance cluster 32 might represent a lie-in, then getting housework done before spending the rest of the day in leisure, while in 18 the housework is mostly put off until after lunch. It is worth noting as well that cluster 32 has a later wakeup time than the others, while the long unpaid workday (21) is the almost exclusive preserve of those with children (Table 4.1).

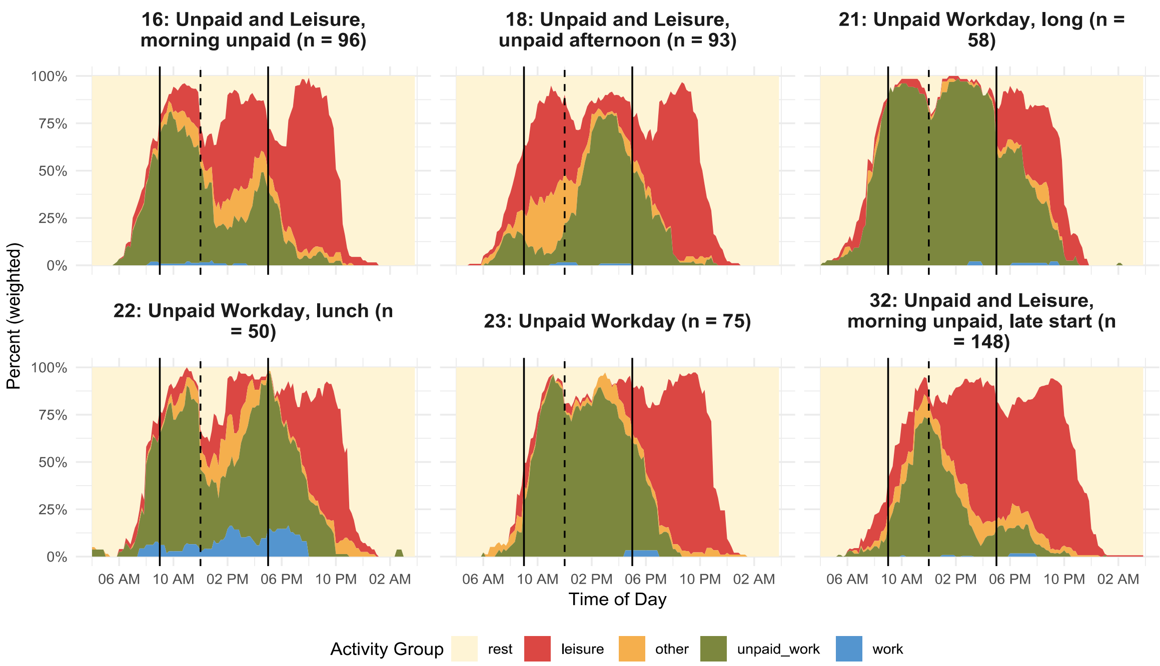

Figure 4.2.1

The most informative angle on these types of day is male-female differences. Figure 4.2.2 shows the percentage of all male and then female diary days that belong to one of these six clusters. Taking the two together, these unpaid workdays as a whole greatly increased in

June 2020 compared to 2016, as a result of the loss of work. But there are differences between women and men. For women, the rates of all clusters except for 32 remained constant, and the extra came entirely from this cluster, which might therefore (although the sample size to establish this is not available) reflect a schedule of unpaid work preferred by women newly forced into more such days by lockdown. Meanwhile men, very unlikely to do any of these unpaid workdays in 2016, increase their rate of almost all of them, not only cluster 32 but also the more structured workdays. In August 2020, all of these days show a slight decline as people return to work, although rates of 16, 18 and 21 are more constant.

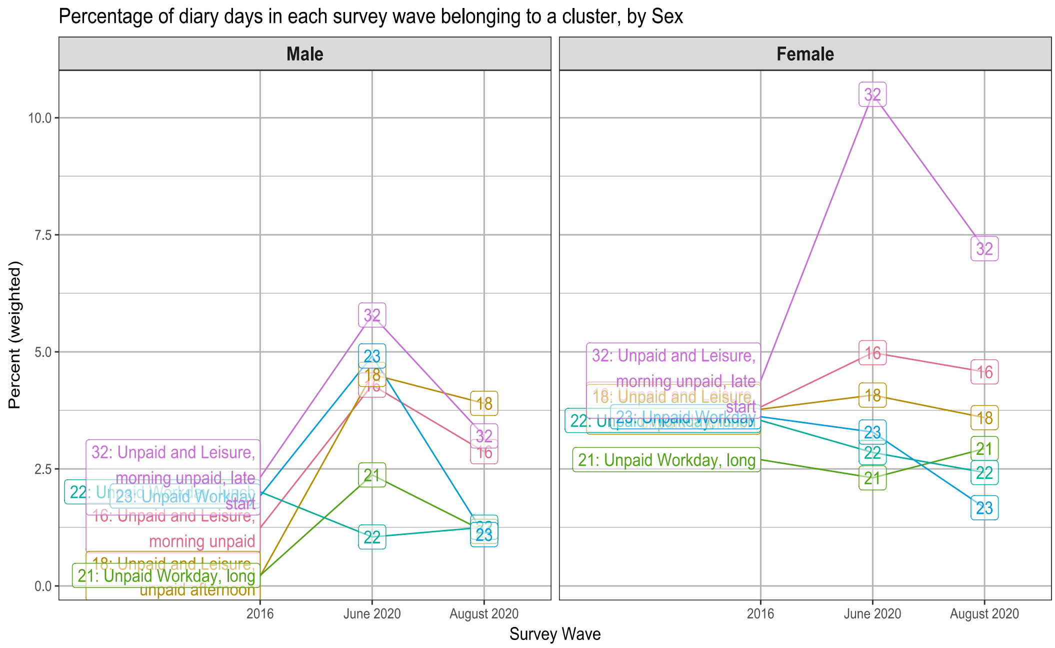

Figure 4.2.2

Model 4.2.1 models the probability of a diary day belonging to the groups ‘unpaid workday’ (21-23), ‘unpaid and leisure’ (16, 18) and cluster 32 separately, in terms of the interaction of male-female and survey wave. It is a categorical model with softmax link, like Model 4.1.1 above (details in Appendix C) except that the outcome probability is measured in terms of all diary days, so the impact of differential loss of work is reflected in the model outcomes and the assessment of male-female inequality. Class and age group are included as control variables, which is particularly important here because in the dataset the class groups are strongly divided by sex: ‘Higher administrative and professional’, along with ‘Routine’, are strongly male, while ‘Intermediate’ and those not working are strongly female (see section 3.3 and Appendix A for explanation of the class grouping). The results are shown in Figures 4.2.3 and 4.2.4.

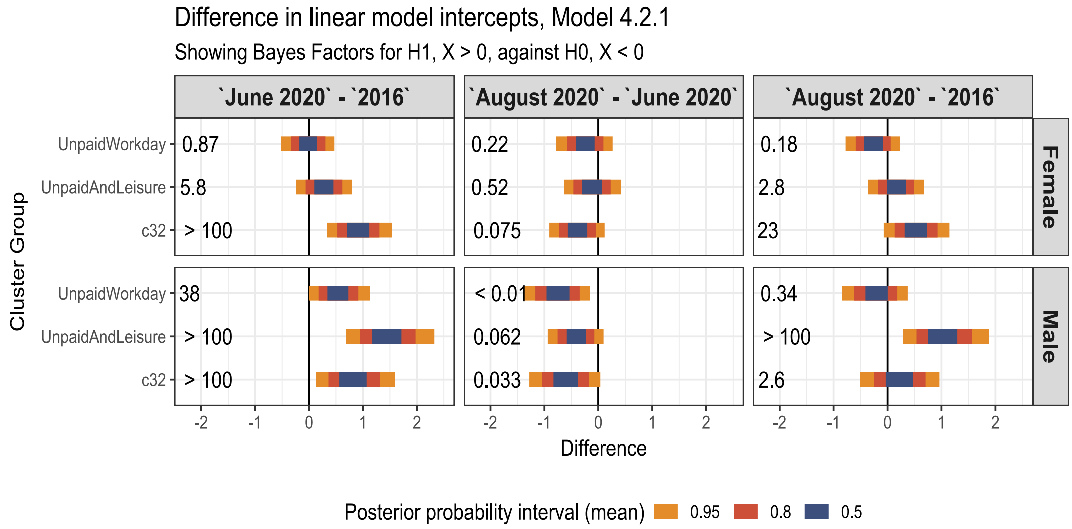

Figure 4.2.3

Figure 4.2.3 shows the results of Model 4.2.1 in terms of the difference between survey waves. Comparing June 2020 with 2016, it confirms with strong evidence that Cluster 32 has increased for both men and women, and other kinds of unpaid workday only for men; only moderate evidence (Bayes factor 5.8) is found that 'Unpaid and Leisure' days have increased for women. Meanwhile moving from June to August, Cluster 32 and Unpaid Workdays have decreased for men, and as well as only moderate evidence for 'Unpaid and Leisure' shown by the Bayes Factor of 0.062 in favour of a decrease.

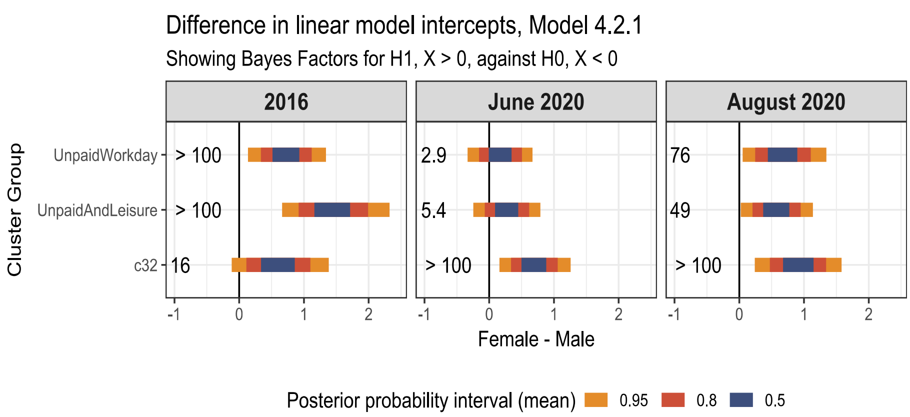

Figure 4.2.4

Figure 4.2.4 shows results from the same model, but looks instead at the male-female difference, for each survey wave in turn (so that a positive value means that women were more likely to have such and such a daily routine). In 2016, women's days were more likely than men’s to be an ‘unpaid workday’ or a mixed unpaid-leisure day, and perhaps cluster 32, this last with moderately strong evidence on the Bayes factor, though the credible interval at 95% overlaps 0. In June 2020 however, men’s increase in most kinds of unpaid work day (Figure 4.2.3) meant that evidence for male-female inequalities only persisted in rates of cluster 32; however by August the pre-existing inequality was re-established, for all types of day. The pattern of inequalities had however shifted compared to 2016: cluster 32, instead of the other two groups, became the unpaid work schedule that women were most more likely to have compared to men.

As already discussed, however (section 1.1), the form of *anomie* experienced by those who continued to work in lockdown, and those who did not, was rather different. Model 4.2.2 adds the interaction variable ‘in work’, which records whether the respondent was working or not at the time. Whether the diary day is a workday is controlled for, to correct for the fact that those not working of course are more likely to have one of these – not work – daily routines. Considering the differences in linear model intercepts between those working and those not for Model 4.2.2 therefore allows assessment of whether those who stopped work (and so who may have experienced, in a sense, a greater *anomie* of time use) , were more or less likely to adopt one or the other of these daily routines on days they were not working, compared to those who continued to work during lockdown.

These differences are shown in Figure 4.2.5, so that a positive value indicates that those working are more likely to have such and such a routine than those not working. None of these are credible at 95%, reflecting how the small sample size of the model does not quite allow the analysis to distinguish between groups of this size. Nevertheless, there is moderate evidence for some differences. In June 2020, women who were not working were more likely to have a daily routine in cluster 32, or in the mixed unpaid and leisure clusters, suggesting that these forms of semi-structured half-unpaid half-leisure days were part of the response to lockdown of those who were not working, and it is this group who drive the effects shown in Figure 4.2.3. Meanwhile, in August 2020, it is on the contrary those in work who are more likely to belong to cluster 32 – and men who are not working.

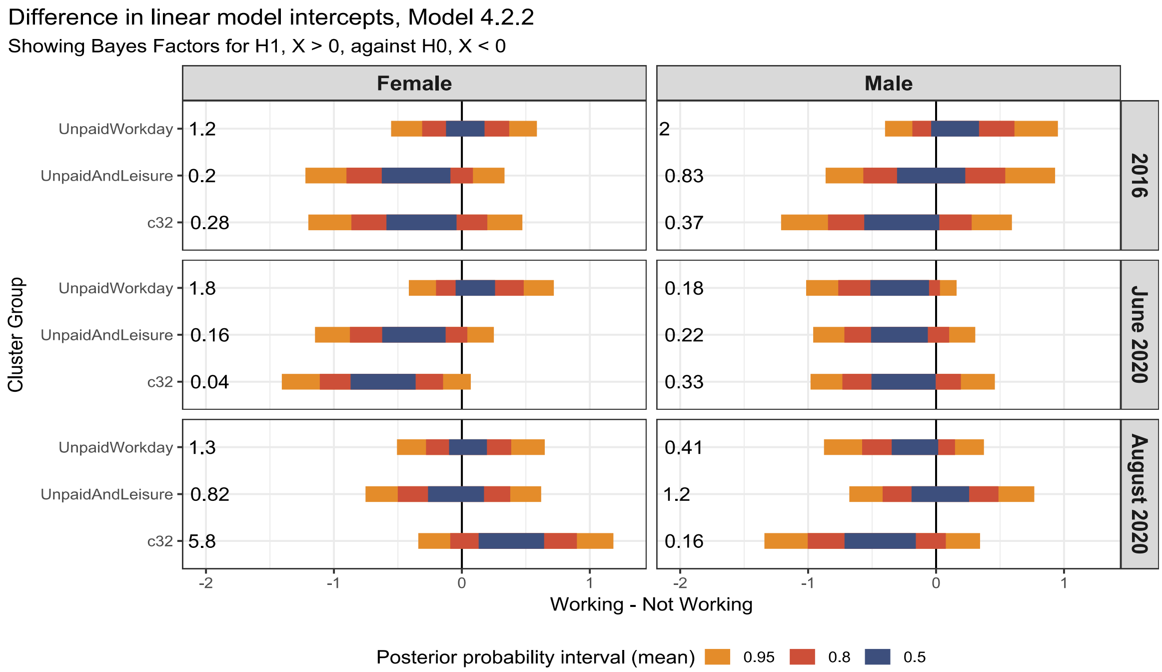

Figure 4.2.5

Taking all these results together, while all of these unpaid workdays can be said to be typical of lockdown in June 2020, in particular cluster 32, there are male-female differences in how these days were structured. Unpaid workdays with the most unpaid work and the strongest structure to the day, clusters 21-23, were part of the male response to lockdown, while remaining typical of women both before and after who (perhaps) maintained their daily schedule. Meanwhile cluster 32, where a lie in is followed by a single main period of unpaid work, seems to characterise the female response to the demands of unpaid work in June 2020, in particular among those who stopped paid work, and this daily routine persisted into August 2020. Figure 4.2.3 also implies that by August 2020, women's unpaid workdays had shifted slightly from the fuller clusters 21-23 to the more leisure dominated 16, 18 and 32. It might be thought surprising that the fact of living with children was not included as a control variable; in fact, it changes the results very little. This is because, as will be shown in section 5.2 below, childcare tends to be entered on the secondary activity vector, which is not taken into account here.

4.3 Leisure Days

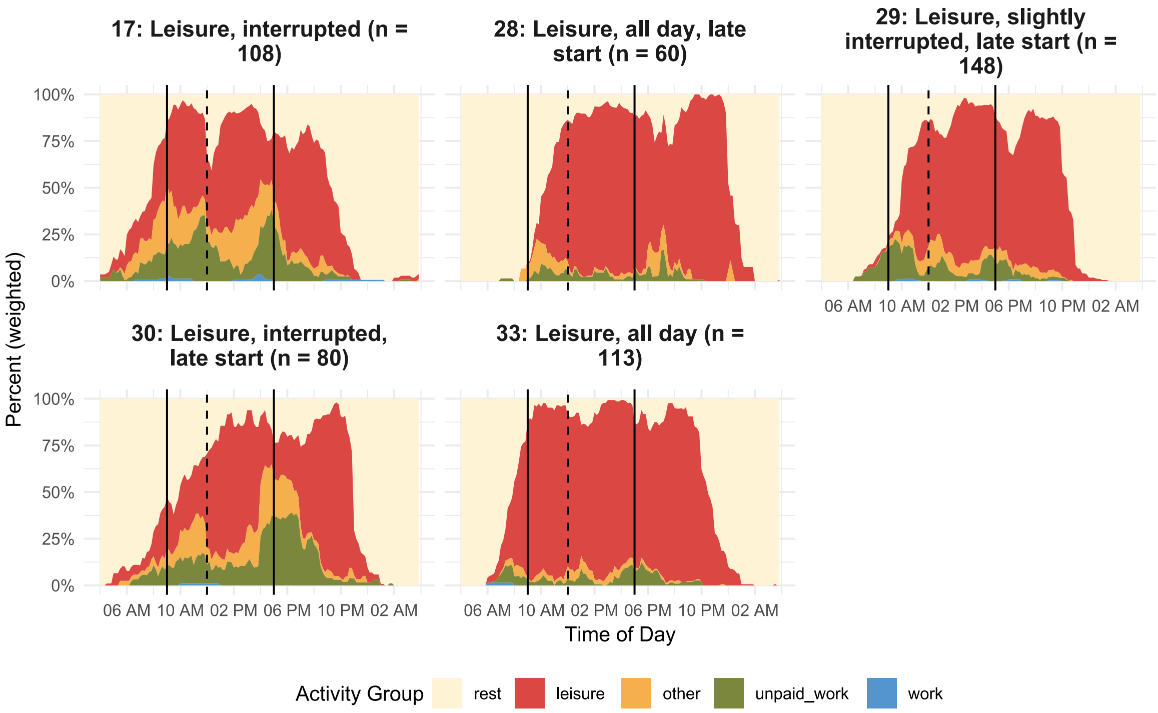

Figure 4.3.1

Figure 4.3.1 shows the clusters which are dominated by leisure activities. Clusters 28-30, like cluster 32 in Figure 4.2.1, but unlike clusters 17 and 33 here, have a late start, that is a lie-in. The proportion taken up by unpaid work and other activity reflects the extent to which the days in the cluster were interrupted by unpaid work tasks (and not, as explained above in the introduction, that some people in the cluster spent all day doing unpaid work). So clusters 17 and 30 are days primarily devoted to leisure activities but with frequent interruptions by the demands of housework and childcare, while clusters 28 and 33 are relatively tranquil. All the daily routines here are accordingly distinguished from the Unpaid 'Workdays' in Figure 4.2.1 not only by the amount of unpaid work, but also by the degree to which it is scheduled (in fact, clusters 17 and 30 here have about as much unpaid work as clusters 18 and 32 above). Unpaid work in these clusters appears unscheduled and intermittent, interruptions in the day, unlike cluster 32 in Figure 4.2.1 where unpaid work is relatively scheduled so that 75% of respondents are performing it at midday. Two final notes are that clusters 17 and 29 more often contain meal breaks, with almost 50% of cluster 17 taking lunch at midday, while on the whole, in this set of six clusters more unpaid work implies fewer waking hours.

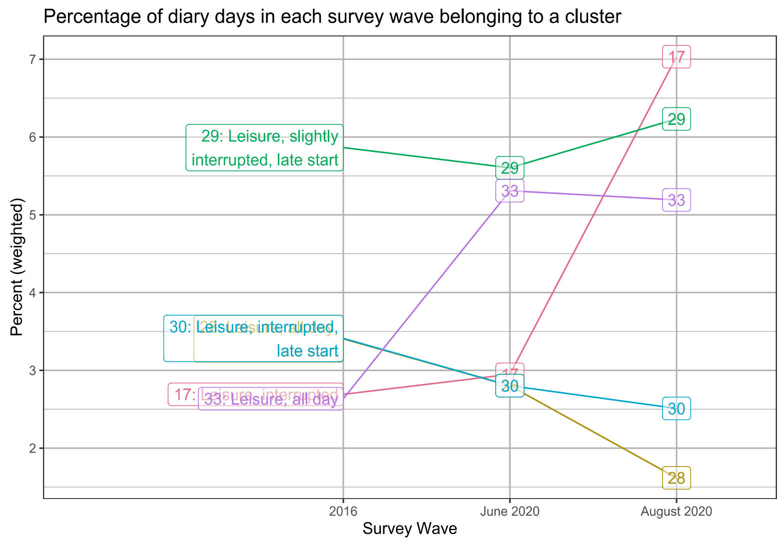

Figure 4.3.2

Figure 4.3.2 looks at the difference in the rates of these days over lockdown, again as a proportion of all days and so incorporating the effect of the decrease in workdays. It can be seen that while the decrease in workdays was compensated by an increase in these 'leisure days', only two of them in fact increased: 17, which is most filled by unpaid work interruption, and 33, the least interrupted. What these two have in common is that they are the most early starting leisure days, as if people without organised work or unpaid work commitments got up as early as possible in order to fill their day with leisure activities.

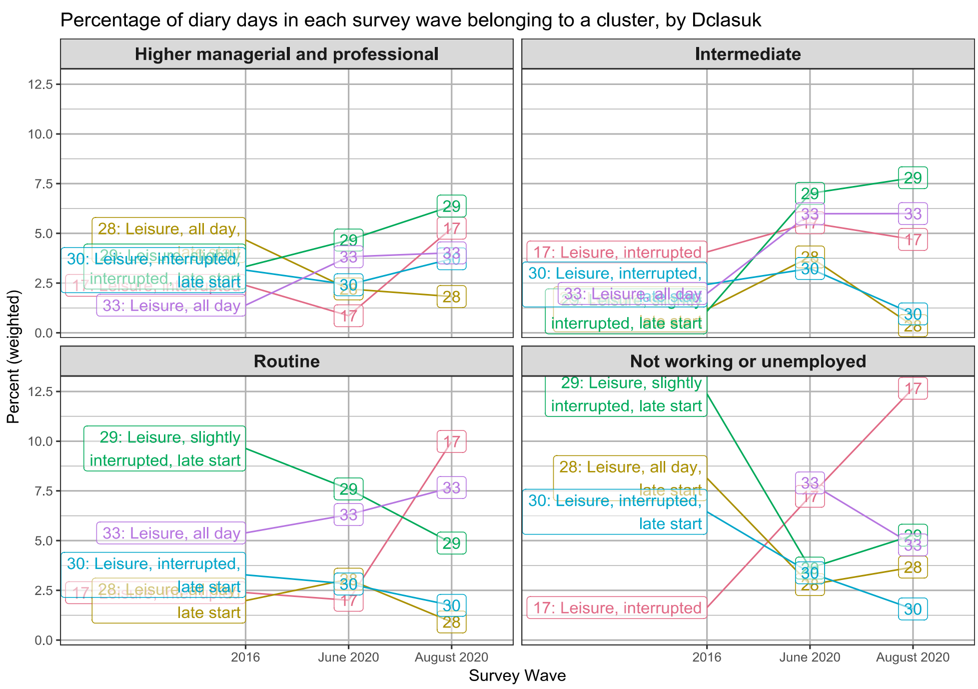

Figure 4.3.3

There is a class effect in how leisure days are spent in lockdown, a contrast between clusters 29 and 17. Figure 4.3.3 shows that cluster 29 decreased for those in ‘Routine’ occupations, the long-term unemployed and inactive people, but increased for those in ‘Higher Managerial and Professional’ along with ‘Intermediate’ occupations. Meanwhile cluster 17 increased for all groups, but much more strongly for the ‘lower’ two classes. The key difference between these two clusters is once again wakeup time, and this result points to a class division in reactions to lockdown in this regard. This question of wakeup time and its link to class and educational inequalities will be explored more deeply with models in section 7.1.

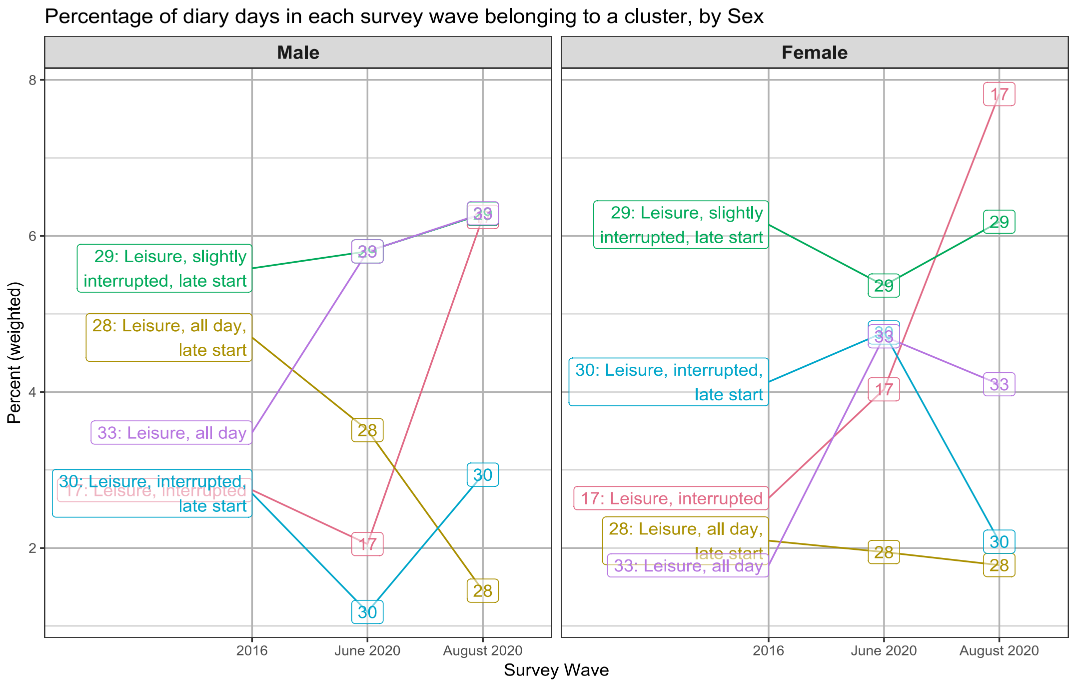

Figure 4.3.4

Turning to the association of these daily routines with male-female inequalities in Figure 4.3.4, once more the obligations of housework and childcare appear unequally distributed between men and women, this time in the form of the interruption of leisure time by unpaid work tasks. Women’s days are much more likely to be in clusters 17 and 30, the most interrupted, especially in June 2020, while men have a greater proportion of the less interrupted days, clusters 28 and 33, although this difference slightly decreases in lockdown as women increase their amount of non-interrupted leisure days. Cluster 29, which has an intermediate position, is fairly equally distributed.

Model 4.3.1, fits a softmax regression to predict the likelihood a day belongs to a cluster for men and women over each survey wave, again controlling for class and age. The results shown in Figure 4.3.5 (as Model 4.2.1 above; full results are in Appendix C) confirm that cluster 29 ('slightly interrupted') is equally distributed by gender, while the interrupted leisure days (17 and 30), not necessarily unequally distributed before lockdown, come to characterise male-female inequalities in June 2020, as women's time remains interrupted by unpaid work even on lockdown days primarily devoted to leisure. There is furthermore moderately strong evidence that an inequality in uninterrupted leisure days (clusters 28 and 30) persists from 2016 into June 2020, and only moderate evidence in August 2020, although the credible interval for these coefficients just overlaps 0 at 95%.

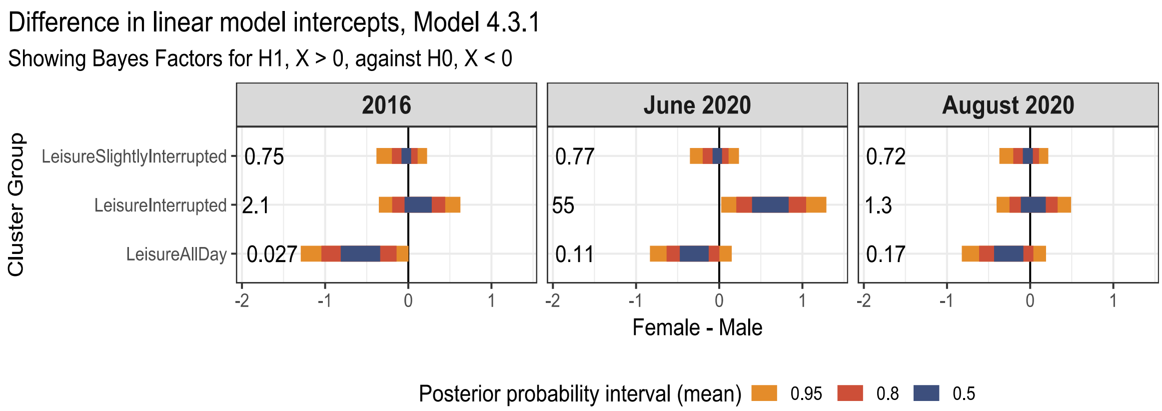

Figure 4.3.5

Figure 4.3.6 shows the results of Model 4.3.1 in terms of the difference between survey waves. It can be seen that there is little evidence for a difference in rates of these days among women in particular: only moderately strong evidence (with credible interval overlapping 0 at 95%) for 'Leisure All Day' in June 2020 compared to 2016, and for interrupted leisure days cumulatively over the two survey waves. Comparing Figure 4.2.3 above, there is much stronger evidence that the mixed day of cluster 32 is a typical female response to lockdown. Among men, meanwhile, the shift is in leisure days interrupted by unpaid work, for which there is extremely strong evidence of an increase in August 2020 compared to June. This perhaps therefore reflects a daily routine taken on by men when their housework demands increase as their partner returns to work but not themselves.

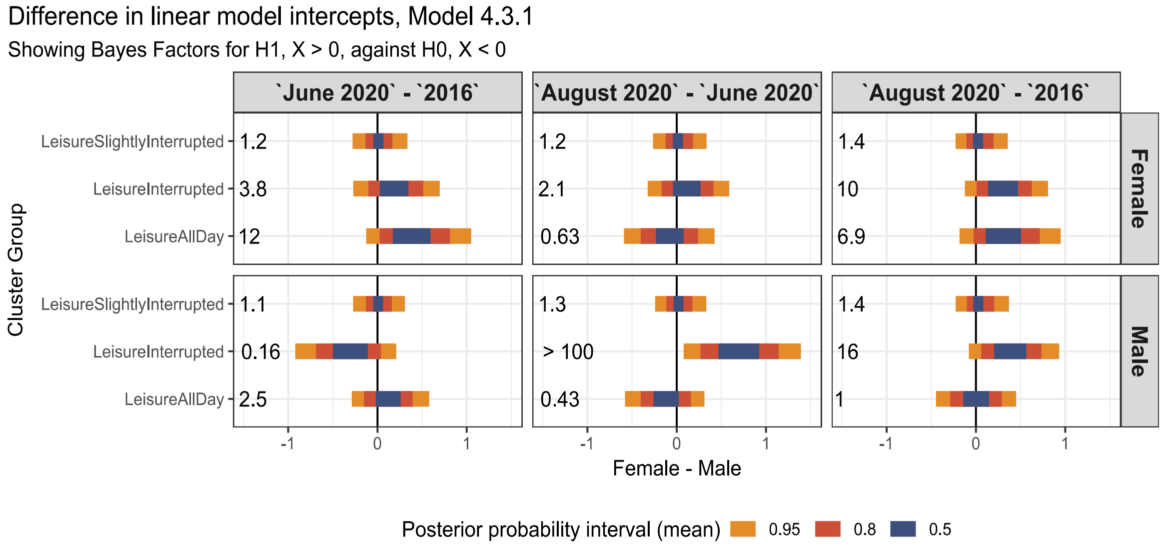

Figure 4.3.6

Model 4.3.2 adds the interaction predictor to Model 4.3.1 of whether the respondent was working, as well as controlling for whether the diary day was a workday, so that the fact that those in work of course have fewer of these non-workdays is taken into account. Like Model 4.2.2 above, it allows an appreciation of the differential response to lockdown among those who were working, and those who stopped work, shown in Figure 4.3.7 (Full results once again are in Appendix C). While all the intercepts overlap 0 at 95%, this shows that there is little evidence that reactions to lockdown were differentiated between the two groups. It can nevertheless be seen that there is moderate evidence that 'Leisure slightly

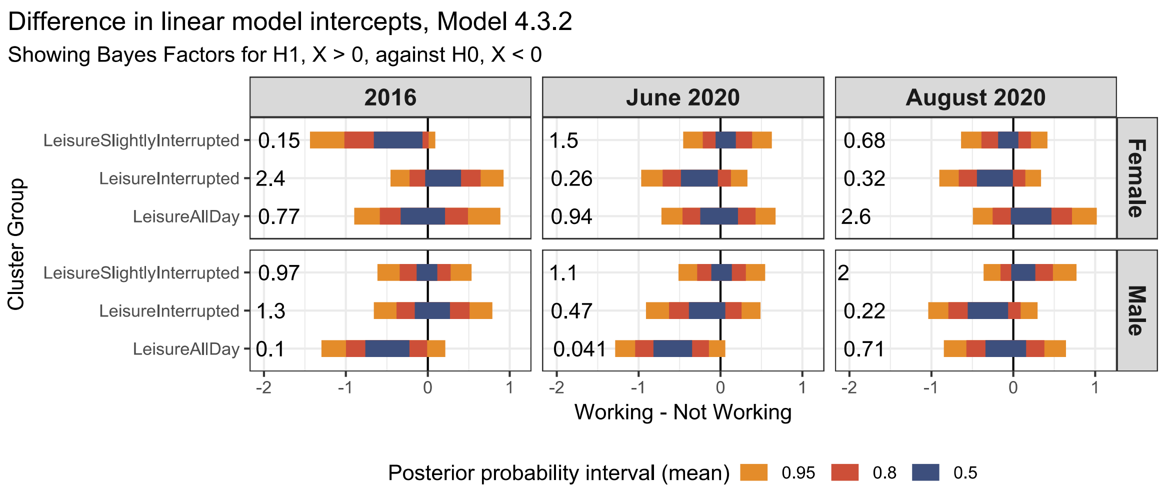

Figure 4.3.7

interrupted' (cluster 29) is more common among not-working than working women in 2016, and that 'Leisure All Day' (clusters 28 and 33) is more common among men not working. In the 2020 waves, the only difference for which there is strong evidence is that 'Leisure All Day' is more common among men not working in June 2020. It seems that this is not a form of typical 'lockdown weekend' but a routine typical of those for whom work time no longer has a place in their week.

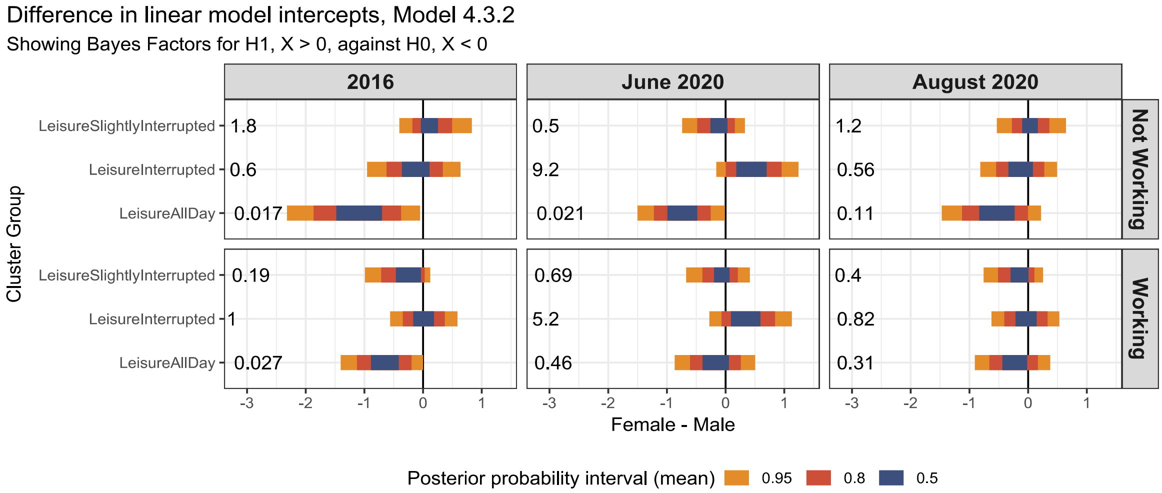

Figure 4.3.8

Figure 4.3.8 meanwhile shows the how the differences between men and women shown in Figure 4.3.5 are different between those working and those not. While the inequality in days of interrupted leisure in June 2020 appears equally distributed between those working and those not, there is a difference for the uninterrupted leisure clusters for this survey wave. It would seem that one of the effects of lockdown was to increase the proportion of women in work, but not out of work, who had such uninterrupted leisure days, reducing the inequality between men and women among those who remained in work only.

Looking at the relation between typical daily schedule, interruption of leisure by unpaid work, structuring of the day and male-female inequalities, it is worth bringing together sections 4.2 and 4.3. The more unpaid work that (presumably) needs to be done, the more structured and less interrupted the day appears, at least at this level where individual tasks are aggregated. Men are less likely to have a day dominated by unpaid work, and when they do it is most usually in the form of a long, well structured day (cluster 23, but in the 2020 waves only), or one with only a few interruptions (cluster 29). Women on the other hand are more likely to either have a highly interrupted day (cluster 17), or to schedule a single time slot where most of the unpaid work is done (clusters 16, 18 and 32), of which the latter tendency increased markedly in lockdown, and the former only in August 2020. They are nevertheless still more likely than men to have a day dominated by unpaid work (clusters 21-23), although this inequality temporarily narrowed during lockdown. There is little evidence, with the size of the dataset available, for differences between those who continued to work in lockdown and those who did not: two exceptions are that cluster 32, a lie-in with single period of unpaid work, appears typical of women out of work in lockdown, while uninterrupted leisure increased in lockdown only for women who remained in work, not those who stopped working.

The question of interruption of the day by housework and childcare will be considered further as part of the wider concept of fragmentation of the diary day in section 5.1. In that section, the interaction of male-female inequalities with children (which is not pursued here firstly because the size of the dataset cannot support it in relation to the detailed outcome of diary day cluster, and secondly because it is often entered on the secondary activity vector which is not taken into account in the clustering) will also be considered.

4.4 'Disrupted' days

I have chosen to apply the term 'disrupted' to days in which the pattern of waking and sleeping is far shifted from the norm in all other typical daily routines seen so far, without wishing to imply that these routines were disrupted by anything in particular. These typical daily routines are shown in Figure 4.4.1. All of these routines furthermore display high rates of non-synchronicity in activities, as shown by the horizontal rather than vertical bands in the tempograms (cf. discussion of Figure 4.1 above).

Overall these days are characterised by short periods of different activities in no particular order, and by long periods of sleep. Clusters 19 and 20 most resemble other daily routines, as the majority sleep overnight. Cluster 19 involves a late wakeup and/or an early bed with frequent napping, and is mostly characterised otherwise by unpaid housework. Some members of cluster 20 are active for some portion of the night, and nap during the day, although most activity is still concentrated in the daytime. Turning to clusters 26 and 34 that ceases to be the case: 34 involves those who by and large sleep in the morning and during the day, before an evening of leisure and intermittent overnight activity; 26 contains intermittent daytime activity before a brief arousal from rest and sleep for a brief burst of leisure activity in the evening. Cluster 35 is hyperactivity, with very little sleep involved, while cluster 27 and 37 are days filled with rest, in 27 only interrupted by one period a day or so of other activity. (It is worth noting that cluster 37 has very high rates of completion for secondary activity, perhaps indicating a different attitude to the questionnaire, cf. Sections 2.1 and 5.2). Although the activity patterns shown might seem extreme, with the exception of cluster 27 the number of respondents in each cluster are by no means small compared to many of the others studied so far.

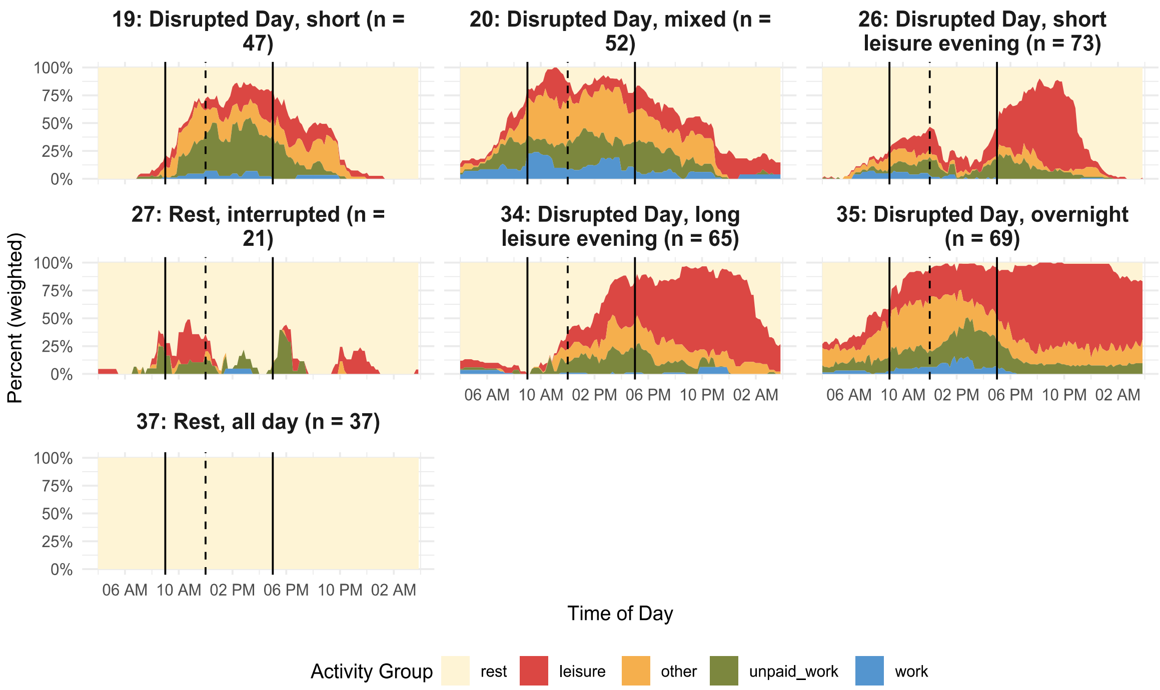

Figure 4.4.1

Figure 4.4.2 shows the change in proportion of all diary days belonging to these categories. What might be surprising is that even in 2016 rates of these days were by no means negligible, and only three rose greatly in the June 2020 wave: clusters 26, 34, and 35. Cluster 27 rose slightly into August 2020 while all the rest returned to pre-lockdown levels. Model 4.4.1, of the same softmax type as the others used in this section (Model 4.2.1, Model 4.3.1), controlling for age, sex and class, confirms this result; the effect for cluster

35 is particularly well established, as well as cluster 26, while the effects for clusters 34 and even less 27 are supported by strong evidence, but not quite credible at 95% (see Figure 4.4.3, with full results in Appendix C). With controls, there also appears to be an increase in cluster 37, in June 2020 compared to 2016, that was not apparent in Figure 4.4.2.

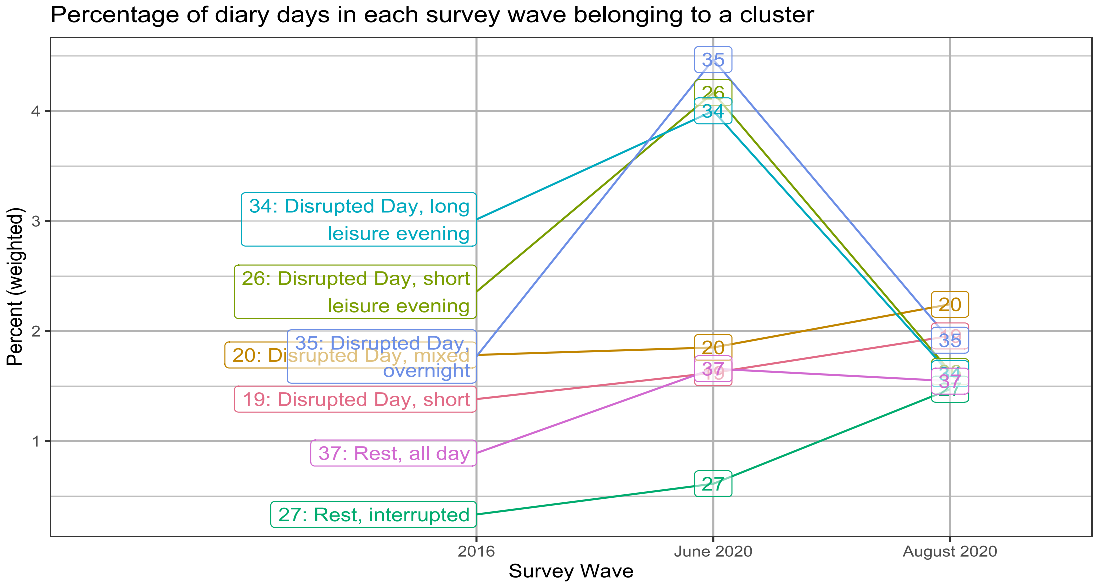

Figure 4.4.2

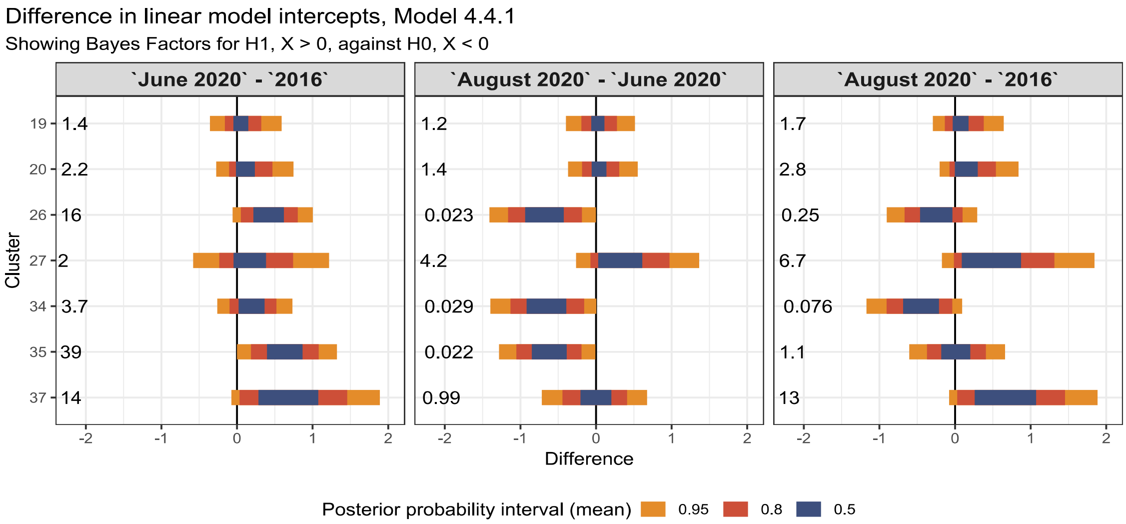

Figure 4.4.3

It would seem therefore that lockdown's effect was to increase the proportion of days that are the most removed from norms of wake and sleep time, enabling day patterns involving sleeping during the day. Clusters 34 and 35 are further characterised by high levels of activity over the day as a whole, implying a sort of scattered productivity. Clusters 19 and 20, involving extended sleep and unpatterned activities but still mostly asleep between the hours of 11pm and 6am, did not increase over lockdown. When the difference between those in work and those not working is considered (not shown here), there is little evidence for any difference between those working and those not in lockdown, except in the case of Cluster 35, for which there is extremely strong evidence that it is more typical of those in work than those not working.

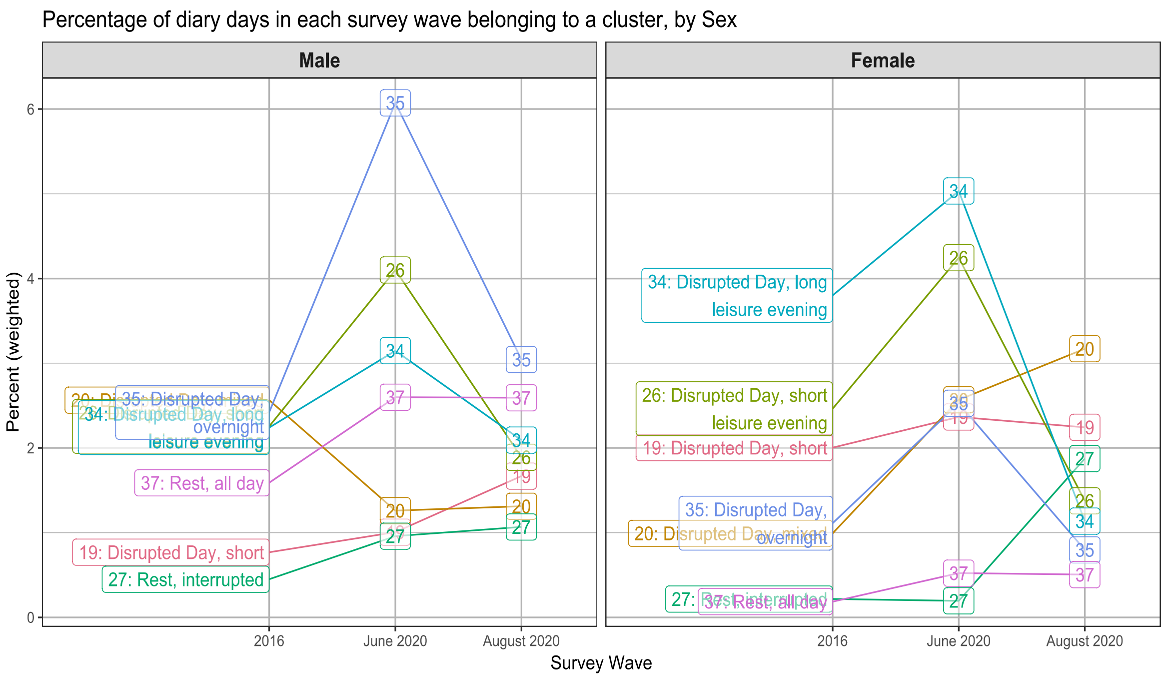

Figure 4.4.4

One particular male-female difference, shown in Figure 4.4.4, appears in this group of daily routines. Men's days are more likely to belong to in cluster 35 and 37. The result for cluster 37, almost unknown for women, implies that (almost) only men are ever free of any kind of daily obligation. (Cluster 37 also has high rates of multitasking, examined in section 5.2, so it also perhaps reflects a certain attitude to the data entry of primary and secondary activities). The hyperactivity of cluster 35 also seems to be a mostly male – lockdown experience. Model 4.4.2, of which results are shown below in Figure 4.4.5 confirms this, controlling for class and age, confirms this result, as men's days are much more likely to fall in one of these two clusters; there is not evidence for an effect for other kinds of disrupted day. There is also a slight effect in Figure 4.4.4 where women are more likely to have days in clusters 26, 27 and 34, but this could not be confirmed by modelling. As in the case of Model 4.2.1, there is no evidence for a difference between those in work and out of work for these clusters (not shown).

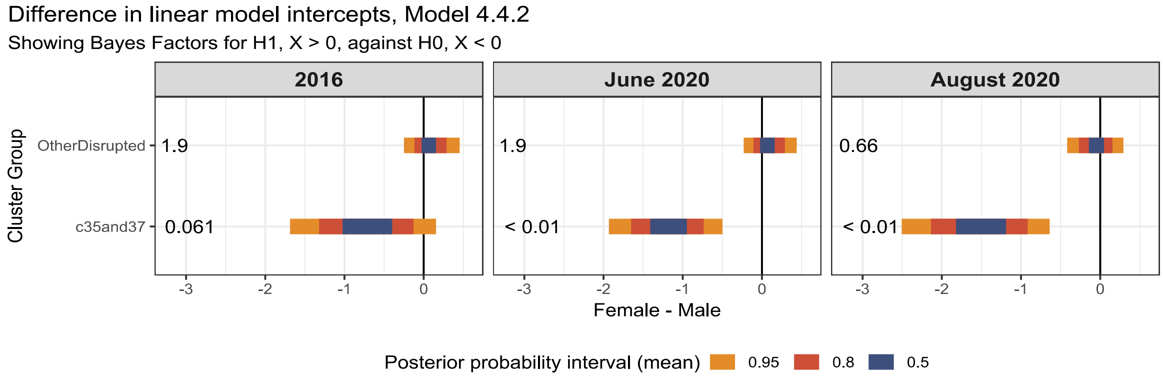

Figure 4.4.5

4.5 Other Typical Days

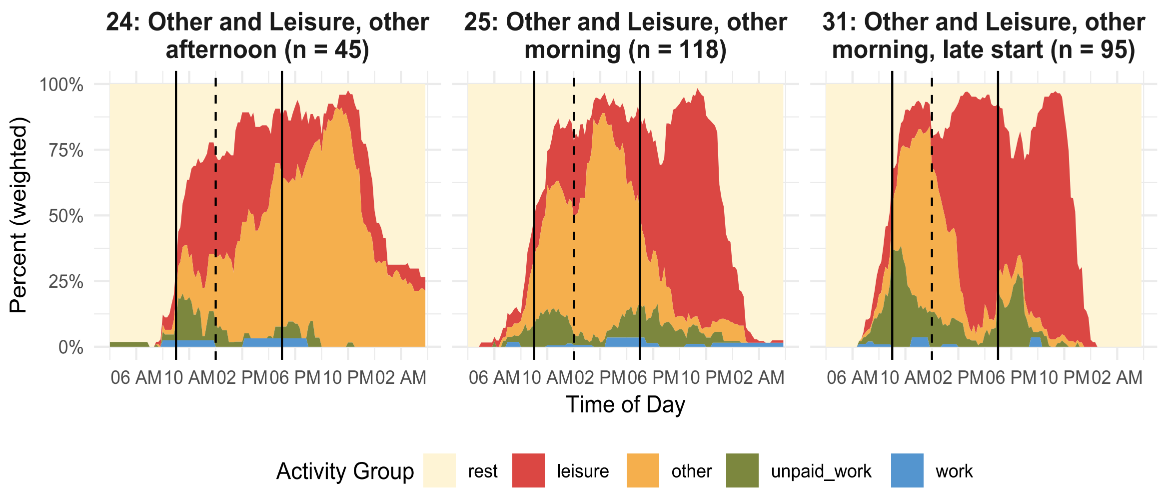

Figure 4.5.1

Figure 4.5.1 shows the remaining clusters, characterised by a large proportion of ‘other’ activity. The activity category ‘other’ is a catch-all, not only containing uncoded activities but also ambiguous categories such as ‘telephone’, ‘shopping’, ‘travel’, where it is not clear whether the activities relate to work, unpaid work or leisure. For this reason, I do not analyse these clusters, and they are presented for completeness only. I would briefly note that Cluster 25 is characteristic of Higher Managerial and Professional Occupations, as well as unemployed and inactive people, in 2016 only; meanwhile cluster 24 is particularly associated with poor mental health, perhaps because of the sleep disruption that is apparent.

4.6 Daily Routine and Mental Health

Two potential links between lockdown and poor mental health are explored in this study. On the one hand, mental health may worsen in lockdown because of the loss of status and the ‘fatalist’ problem of internalising unacceptable norms consequent on stopping work or the increase of housework responsibilities. On the other hand, theorists such as Han (2015) have proposed that over-implication in work and leisure activities can lead to burnout. This latter cause may have been increased by the lack of regulation of time use in lockdown (see discussion above in section 1.4).

The mental health indicator used here is the average of answers to 11 separate questions, producing a continuous scale with 0 indicating improved mental health, 1 indicating no change, 2 indicating worse, and 3 much worse (see section 3.3 for details). The measure is only recorded for the 2020 survey waves, here considered together (giving n = 1455 cases), and are a subjective rather than objective measure of improvement or decline, used here as the best available. Its distribution is irregular, with twin peaks just below 1, and again at 1 due to a large number of respondents responding ‘no change’ for many or all questions.

Model 4.6.1 predicts mental health in terms of diary day cluster. Diary day cluster was the predictor, and work status in lockdown was controlled for (coding described in Figure 3.3). In order to account for housework or childcare responsibilities, the quantity of unpaid work as well as male-female inequalities were considered as further controls; however, these variables are so closely associated with daily routine that using daily routine as a predictor obscures their effect; here they should be considered as a cause of the diary day cluster predictor. The clusters were grouped into six categories, according to the short descriptions of each given above ('9 to 5 with leisure' = all the clusters described as '9 to 5', except those without leisure.) A Gamma distribution, normally used for event-history models, was used to model this outcome variable, not conceptual reasons but because it gave the best approximate fit, and a meaningless hurdle term was included to allow the distribution to be fit to the responses with value 0. Figure 4.6.1 shows 30 samples from the distribution of outcome distributions produced by the model in thin lines, along with the data in a thick dashed line, in order to give reassurance about the appropriateness of the model specification. The main results of the model are given in Figure 4.6.2 (see Appendix C for full results). A negative coefficient corresponds to a smaller value of the mental health indicator, and so better mental health.

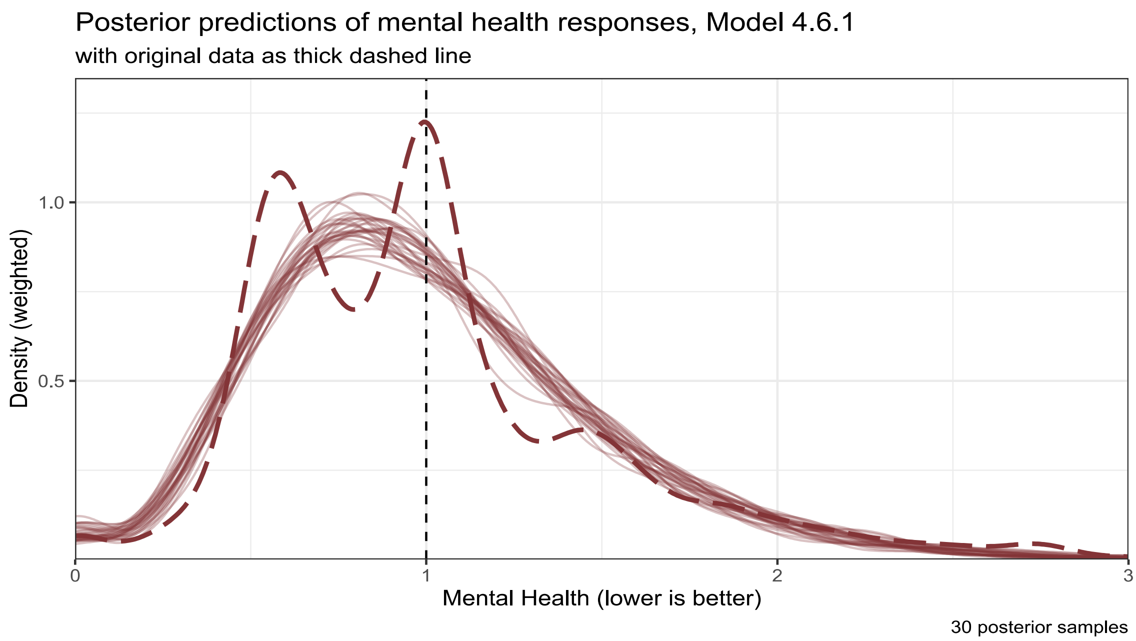

Figure 4.6.1

Model 4.6.1 shows that structured days with clearly defined activity periods are linked to better mental health than unfocused days that diverge more from pre-lockdown norms of routine. Most strikingly, the typical days described as 'Unpaid and Leisure' (see labels in Figure 4.1), a mix of unpaid work and leisure time where the unpaid work is concentrated into a single chunk rather than constantly interrupting the leisure, are associated with better mental health than other non-workdays (both mostly leisure, and mostly unpaid work).

This suggests that a degree of planning and scheduling of unpaid work demands is associated with better mental health. Disrupted days, the days with the least apparent order scheduling, are meanwhile associated with poor mental health, moderately so with a Bayes factor of 9.8, and not credible at 95%. Turning to workdays, there is moderate evidence, again however credible at less than 95%, of a pattern where 9 to 5 workdays, (excluding cluster 9 with no leisure time, which is linked to poor mental health) are linked to better mental health than patterns resembling shift work. As a final, separate point, days with a late wakeup time also associate with better mental health, indicating a link between early wakeup and anxiety.

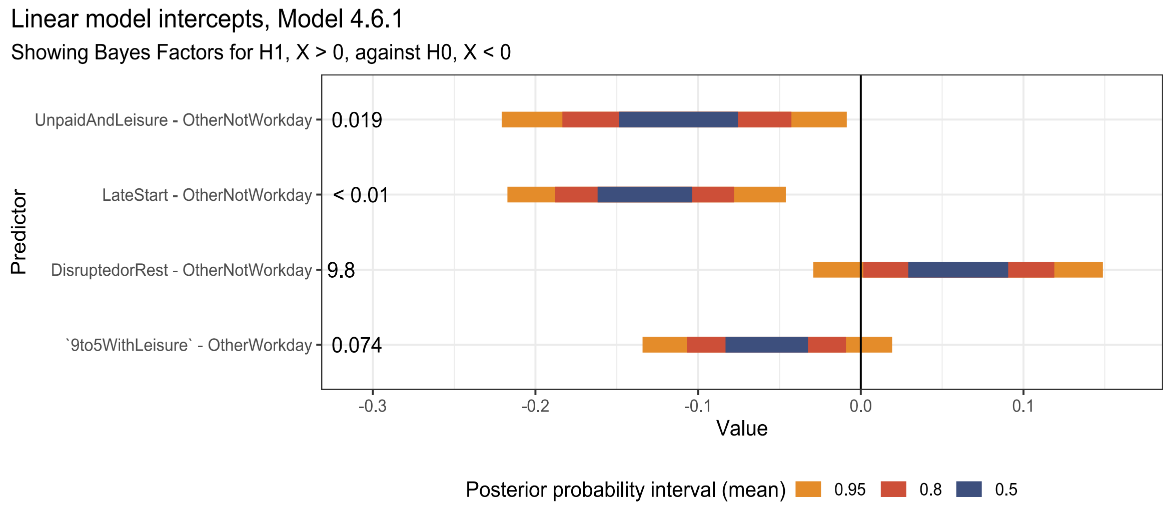

Figure 4.6.2

Taken together, these results indicate that, even when the impact of stopping work is accounted for, people whose daily routines had less structure during lockdown had worse mental health. The causal relationship between the two could be thought to go both ways: poor mental health could cause an inability to control daily routine; or an intense mode of flitting between different activities, unconstrained by norms of regular time use could lead to burnout, as suggested by Han (2015). Another explanation would be that a structured daily routine might contribute to preserving a reassuring sense of normality during lockdown. The data here does not allow distinguishing between the these explanations; the causal relationship could well be mutually reinforcing rather than one way or the other.

4.7 Structuring Daily Routine: Overview

Two main tendencies have emerged from the analysis in this section. Firstly, there are marked differences in the extent to which daily routines are ordered and structured, both in 2016 and during the 2020 waves of the survey. In workdays, while the increase in working from home in June 2020 led to many respondents changing from a 9 to 5 routine towards an afternoon workday, the regular 9 to 5 workday remained very persistent. It is only workers in ‘Higher managerial and professional’ occupations for whom the proportion of non 9-to-5 workdays increased, decreasing pre-existing inter-class inequalities in this regard. Moreover, in August 2020, although rates of working from home had barely declined, those working from home had shifted back towards a 9 to 5 routine. This either reflects a strong tendency to preserve daily work routines, or a (re-)imposition of control over working hours by employers. There is furthermore a slight indication that these 9 to 5 workdays are associated with better mental health during lockdown. Meanwhile, a separate tendency is that long workdays without leisure, almost unknown in 2016, increase through both 2020 survey waves for both home and outside workers. This perhaps reflects a breaking down of the boundaries of work time, along with increased pressure on ‘essential’ workers to work long hours.

In the case of non-workdays, where unpaid housework is combined with leisure activities, there are several forms of day structure: unmitigated leisure; leisure interrupted with unpaid work, to varying extent; leisure with a single chunk of unpaid work; and a full ‘unpaid workday’. This patterning is the result of the combination of structuring the day with the second main tendency in these results: male-female inequalities in the demands of unpaid work. Men did little housework in 2016, most often as slight interruptions in a day dominated by leisure (e.g cluster 29, Figure 4.3.1). In June 2020 they took on more housework, principally in the form of structured full ‘unpaid workdays’, while in August 2020 this increased contribution had begun to decrease. Meanwhile women both before and during lockdown were more likely to have highly interrupted leisure, along with leisure days containing a single chunk of unpaid work which are particularly a feature of the 2020 survey waves, especially those not working in the June 2020 survey wave. The latter is associated with better mental health than the former.

Turning to times of waking and sleeping, lockdown appears to have caused an increase in days where waking and sleeping times are most widely shifted from the norm, but not days characterised simply by longer sleeping hours or more frequent napping. Moreover, wakeup time is furthermore associated with class: those in less qualified professions wake up much earlier during lockdown, even when their day is filled with nothing but leisure. This result is explored further in section 7.1 below.

I suggested above (in section 1) that lockdown can be seen as characterised by an *anomie* of time use. Responses to this *anomie* will result on the one hand from changing obligations of work and unpaid housework, and on the other from choices in spending free time, as leisure or rest and self-care. The preservation, or not, of daily routine will be affected by choices to apply, or not, pre-lockdown routines of time use, whether to maintain a feeling of normality or ensure the day is 'put to use' according to a schedule. It will also, however, be constrained by changing time obligations.

Daily routine as the maintenance of normality, I would argue, is at the root of some tendencies shown here: the return in August 2020 to conventional 9 to 5 work hours even when working from home; and the paucity of 'new' lockdown daily schedules entirely unknown in previous waves. It is further implied by the association of scheduled housework, and by the inverse association of highly disrupted days with better mental health during lockdown (on the subjective indicator available).

Meanwhile, scheduling the day seems to be the cause of many other results in this section: the generalised shift to waking up early on non-workdays; men taking on housework in relatively fixed daily schedules rather than leisure days interrupted with housework; women's preference for getting housework done in a single period of the day (e.g cluster 32) rather than through highly interrupted leisure (cluster 17, in June 2020 only). The increase in very long workdays, and the increase in hyperactive 'disrupted' days' (cluster 35), although perhaps failures rather than successes of scheduling, are perhaps also linked to a desire to use the day as fully as possible. These forms of daily schedule are somewhat linked to poor mental health.

Other results can be ascribed to shifting time obligations in lockdown. The increase in very long workdays, and the shift back to 9-to-5 routines among those working from home in August 2020, may be the result not of worker choices, but of employers' demands. The impact of housework demands is apparent in the strongly different patterning of men's and women's days, supporting previous research which established the effect of unpaid work in fragmenting women's time without looking at daily routine as a whole (Sullivan 1997; Bittman and Wajcman 2000; Sullivan and Gershuny 2018). Although the loss of work in lockdown removed one constraint on people's ability to structure their days as they wished, unpaid housework remained a significant constraint whose differential impact on daily schedules continues to be seen, though in different ways, during lockdown. This will continue to be an important theme in the following section, which examines fragmentation and multitasking during the diary day.

5. Fragmentation and Multitasking

The fragmentation of time, rather than the duration of activities, is an aspect of time use that has become increasingly scrutinised by sociological research. Rosa in *Social Acceleration* (2013, ch.5 and ch.7) contends that the fragmentation of time and of experience is a characteristic of modernity.

On the one hand, fragmentation is part of using time intensely. The diversification of cultural products and an imperative to consume encourages people to fragment their free time between multiple different consumption activities, while norms of 'not wasting time' encourage doing more activities for a shorter duration each, in order to maximise the value extracted from each moment. On the other, time fragmentation is caused by an increasing external demand for individual availability, whether as part of the labour market and 'on-call' jobs, or the intense attention to children that has become expected of parents as part of 'concerted cultivation' (Lareau 2003). Sevilla et al. (2012) provide a measure of empirical support for Rosa's view, finding that fragmentation of leisure activities has increased since the 1960s, particularly for the less educated, while Han (2015) theoretically links the fragmentation of time and experience to mental health consequences as part of 'burnout', as the constant flitting between activities eliminates concentration and repose.

Fragmentation of time may have increased in the *anomie* of lockdown as the decrease in time spent in institutional activities, such as paid work, and the consequent loss of daily routine created free time which could be intensely exploited as the individual would like. On the other hand, the shifting of burdens of unpaid work back to the family, in particular childcare, may also have increased the external demand for individual availability. This latter cause and consequent male-female inequalities has been the focus of previous time-diary research on fragmentation and multitasking. Sullivan (1997) found that UK women's daily time was more fragmented than men's, because of housework interruptions; Bittman and Wajcman (2000), looking at Australia, show that women's leisure activities are more fragmented and involved more multitasking. A slightly divergent view comes from Mattingly and Blanchi (2003), who looking at the USA find that women's leisure activities involve more multitasking than men's, but do not find a significant difference in fragmentation. Sullivan and Gershuny (2018), once more in the UK, find nevertheless that women have more fragmented days than men. And an early study carried out during lockdown, using less detailed data than that available here, has found that women have less uninterrupted work time than men during lockdown (Sevilla et al. 2020).

The concept of time fragmentation may appear in a time diary dataset in two different ways. The most straightforward interpretation is the division of the day into activity periods. For example, a respondent watches TV for an hour, but within the hour takes care of a child for a twenty-minute period: this is entered in the questionnaire as enter 20 minutes TV, 20 minutes childcare, and then 20 minutes TV in the primary activity field. This form of data entry is analysed here as ‘fragmentation’ in section 5.1.

A second way to enter that sequence of activities, however, is to use the secondary activity field: entering 1 hour TV in primary activity, and 20 minutes childcare in secondary activity. This second form of data entry is analysed as ‘multitasking’ in section 5.2. While it could be taken to imply more simultaneous activity, or one activity being constantly interrupted by the other, the fuzzy nature of real life activities mean that the distinction between the two in the data results to a great extent from respondents’ interpretation of the questionnaire. In any case, this form of data entry does imply an interruption and breaking up of the experience of time, and so is very much part of Rosa and Han’s theorisation of time fragmentation. The extent to which the two forms of data entry overlap will be evaluated in the analysis.

5.1 Fragmentation

Here, fragmentation refers to the breakup of the day into activity periods. This can be measured either by the mean length of activity period (e.g Sullivan 1997) or by the number of periods. Here the number of periods is preferred, since it measures the concept of fragmentation (the number of ‘fragments’) more precisely: the mean length of a period is susceptible to being distorted by a single long outlier period. Following the suggestion of Sullivan et al. (2020), a period is defined not as a stretch of time in which the main activity vector does not change, but in which no diary vector changes (including secondary activity, location, people present, etc: see section 2.1). This is in order to better reflect lived experience of time, and has the effect of increasing the number of periods.

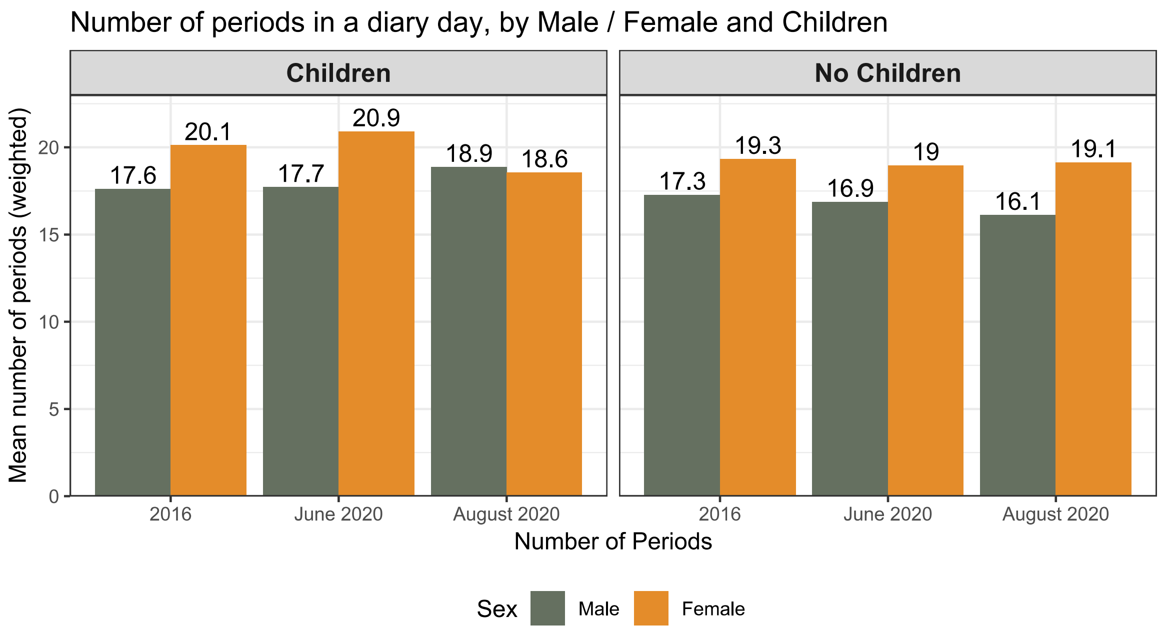

Figure 5.1.1

Figure 5.1.1 shows the distribution of number of activity periods, grouped survey wave, sex (Male / Female) and whether the respondent lived with children. It can be seen that women's time is globally much more fragmented than men's time. This is a well known result (e.g Sullivan and Gershuny 2018), and the cause has long been identified as the demand of household tasks and childcare on individual availability. That is the case in this dataset as well, as Figure 5.1.2 shows: over all three survey waves, though somewhat less in June 2020, the male-female differential in number of periods by activity type (coded as described in section 3.1 and Appendix B) is greatest for the category unpaid work, which is mainly made up of housework.

Returning to Figure 5.1.1, fragmentation is only slightly higher for those with children than those without, indicating that all forms of housework are a cause of fragmentation rather than uniquely childcare. Moreover, any male-female inequality for respondents with children appears to vanish in August 2020; I would suggest that this may be because in households where only one parent returns to work, the other takes on all domestic responsibilities, even when it is the woman who is working. Model 5.1.1 predicts the number of diary day periods in terms of the interaction of male-female, children and survey wave, controlling for age and social class, as well as day type (so as to account for the fact that workdays appear less fragmented because the questionnaire does not encourage entering paid work in a fragmented manner, cf. Section 2.4). It fits a Gamma-Poisson distribution, since the number of periods is the result of a mixture of activities recurring at different rates (see section 3.2). The main results are shown in Figures 5.1.3 and 5.1.4 (full results are in Appendix C).

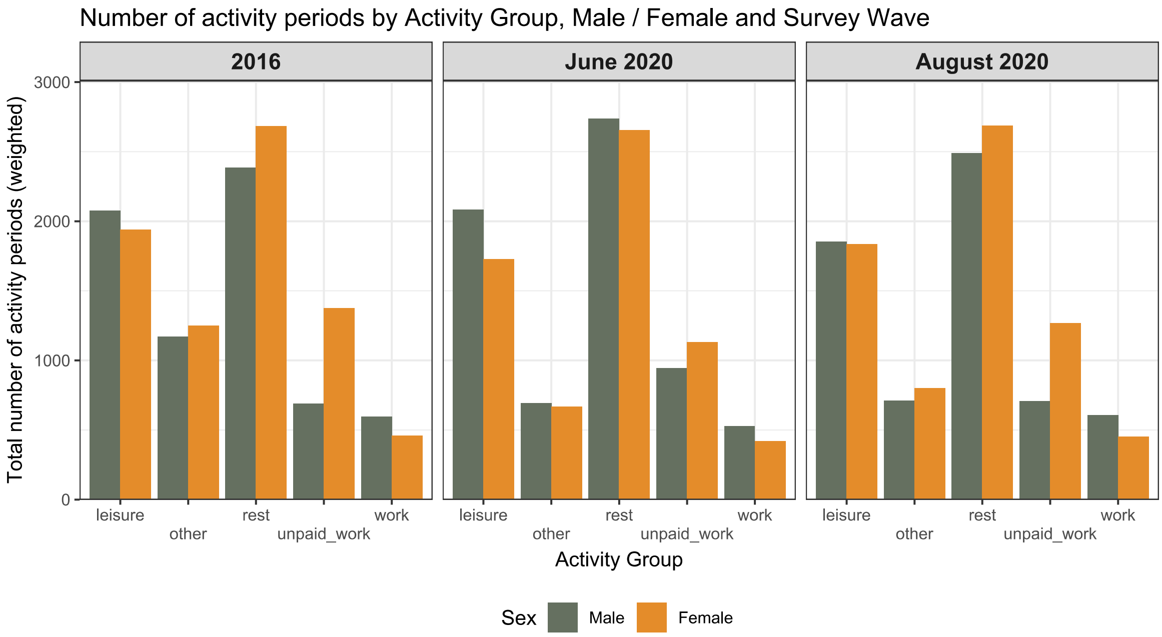

Figure 5.1.2

Figure 5.1.3 shows the difference in the linear model intercepts between women and men, so that a positive value indicates that women's time is more fragmented. There is strong evidence, with 0 outside the 95% credible interval, that women's time is more fragmented in all survey waves without children, even when as here the fact of working or not is taken into account. Meanwhile with children in fact the effect is less clear: there is moderately strong evidence for a difference in 2016, though not credible at 95% (although the pre-lockdown inequality is well established by parallel research such as Sullivan and Gershuny 2018), and in August 2020 there is apparently no difference at all, favouring men if anything.

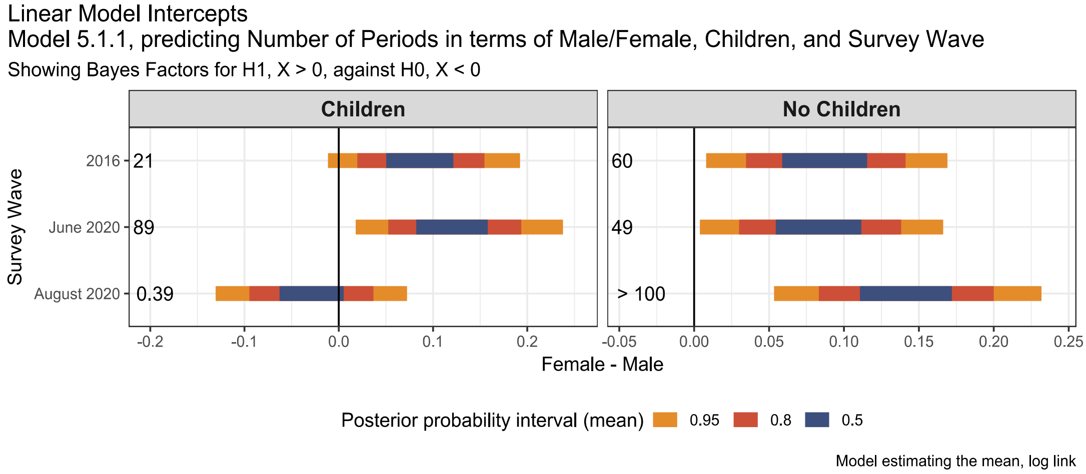

Figure 5.1.3

In Figure 5.1.4, which shows the difference in intercept predicting the mean between those with children and those without children (so that a positive value indicates that children are associated with a more fragmented day) we see that in the first two survey waves barely indicate that children increase time fragmentation, with no difference credible at 95%, and strong evidence only for women in June 2020. Meanwhile the effect where men's time becomes more fragmented is credible at 95% in August 2020.

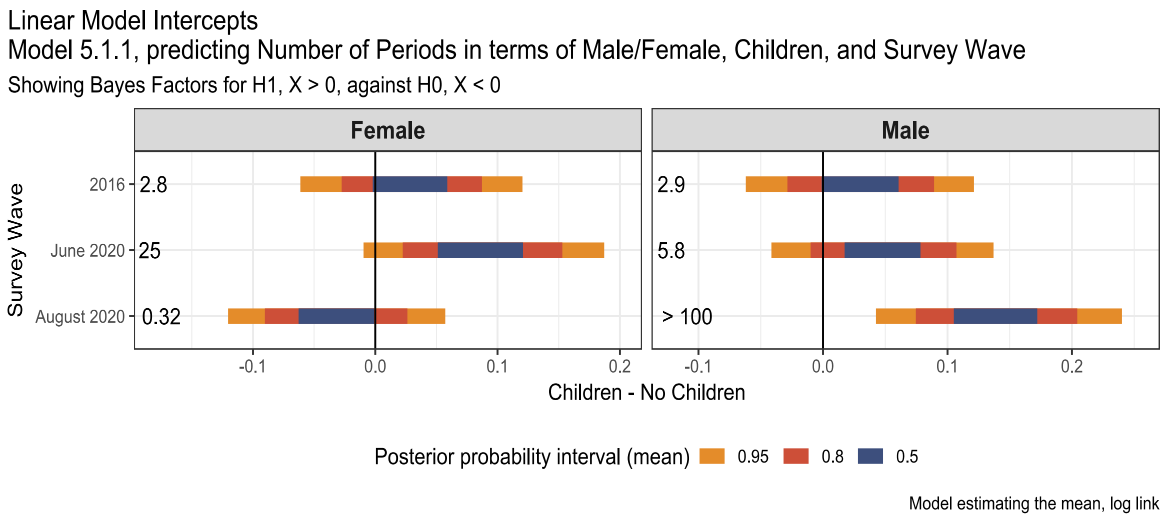

Figure 5.1.4

Overall, the principal effect of housework and childcare on fragmentation of time during lockdown is a maintenance of existing male-female inequality for women without children, increasing in August 2020 compared to June. On the other hand, for those with children, men find their time much more disrupted during the relaxing of lockdown restrictions in August 2020, decreasing male-female inequality for those with children. This is the only change across survey waves that is supported by strong evidence: the Bayes factor for a decrease in the difference between men and women's time fragmentation in August 2020 compared to 2016, for those living with children, is 16.5 (not shown). It seems that the effect of the demands of unpaid work on time fragmentation during lockdown (the June 2020 survey wave) has been limited, especially in the case of those with children. Combined with Figure 5.1.2 above, this would suggest that fragmentation on the primary activity vector principally reflects inequalities in housework as opposed to childcare. Changes to male-female inequalities took place as restrictions eased in August 2020, which I would suggest are the result of only one partner in a household returning to work (relevant variables to verify this inference are not available in the dataset).

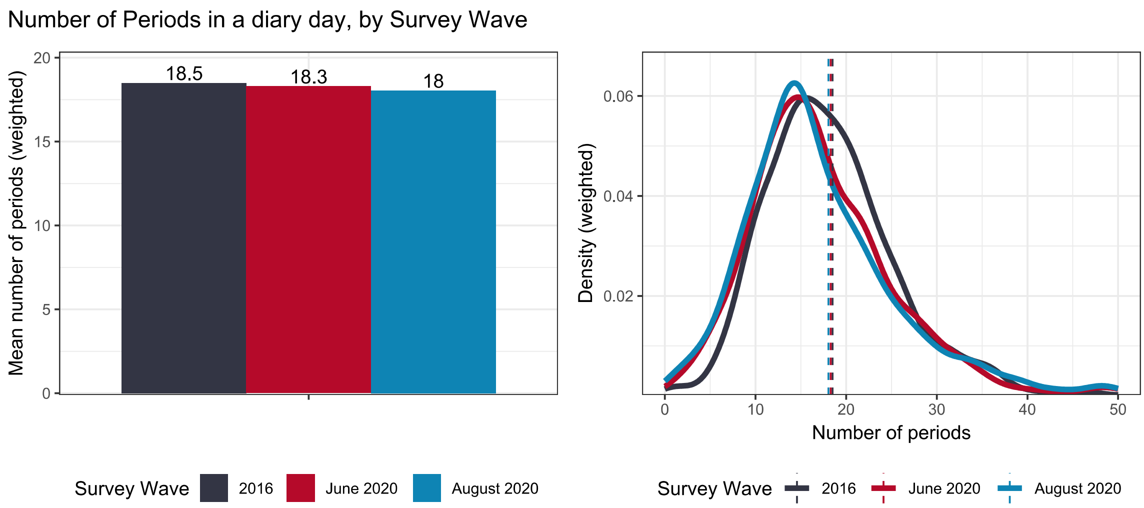

Figure 5.1.5

Moving from the demands of unpaid work to consider time fragmentation in lockdown more widely, Figure 5.1.5 shows a result that is rather surprising in light of the hypotheses of increased time fragmentation advanced in the introduction to this section. There is in fact little change over the survey waves in the mean number of daily activity periods, from 18.5 in 2016, to 18.3 in June 2020 and 18.0 in August 2020 (which does not imply a credible difference in the population of reference: Figure 5.1.6 below). However, that is not the end of the story. Looking at the distribution rather than simply the mean, in the right panel of Figure 5.1.5, sheds more light. The distribution of the number of activity periods changed shape in the 2016 waves, so that while the mean hardly changed, there was both an increase in days with fewer periods and a corresponding increase in days with very many periods. The shift to a more polarised distribution is statistically significant: Model 5.1.2 fits a Gamma-Poisson distribution to these figures, in this case predicting not only the mean, 'mu', but also the 'shape' of the distribution in terms of survey wave, controlling for age, gender, class and having children, as well as working from home.

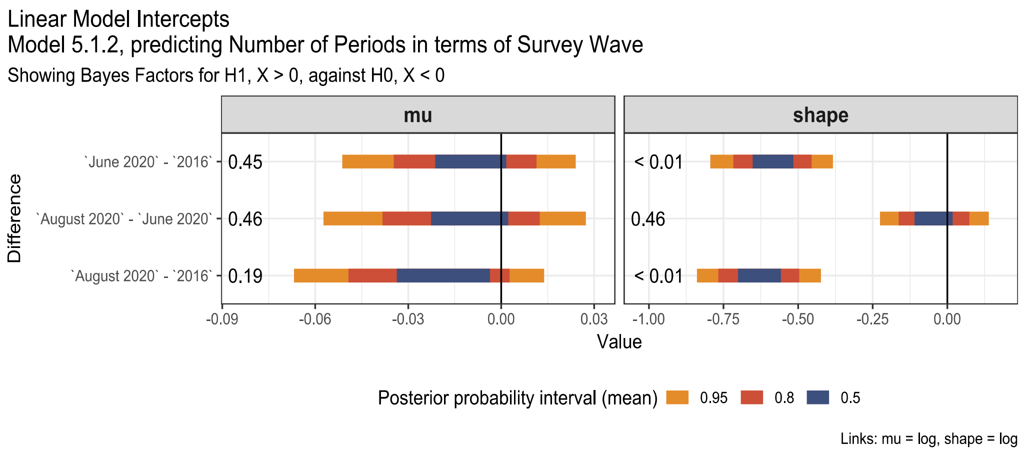

Figure 5.1.6

Figure 5.1.6 summarises the main results in terms of the difference between survey waves (full model results are in Appendix 2). It finds no evidence for a difference in mean ('mu'), but strong evidence for a difference in the 'shape' parameter (the mixing of the Poisson distributions, somewhat analogous to a standard deviation) between 2016 and the two later survey waves.

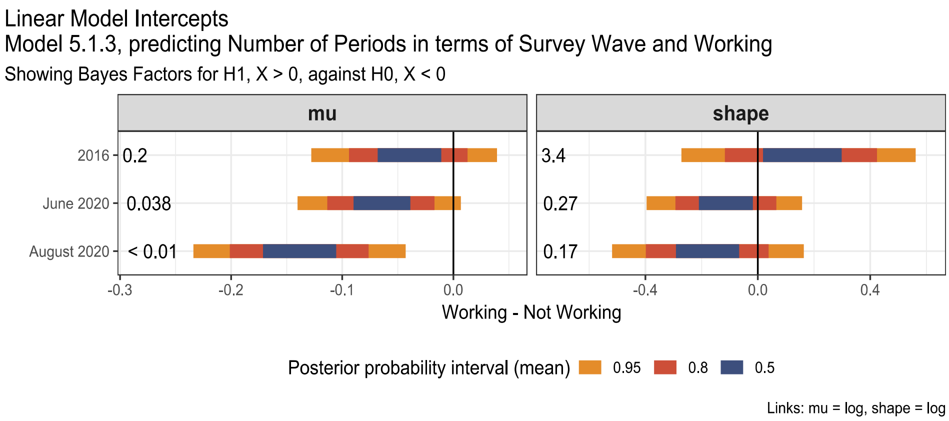

Figure 5.1.7

A supplementary effect can be found when contrasting those who are in work and those who are not. Model 5.1.3 re-fits Model 5.1.2, adding whether the respondent was working, or had stopped work, as an interaction predictor, while also including whether the day was a workday as a control, to look at the effect on behaviour separately from the reduction in the number of activity periods created by the large block of paid work. Full results are in Appendix C, while Figure 5.1.7 shows the difference in intercept between those working and those not working. While in 2016 there is little if any evidence that the average or spread of diary day periods is any different between the groups, there is strong evidence that the average number of activity periods is less for those in work in June 2020, and very strong evidence for August 2020. It seems that lockdown has led to an effect where those not working had more fragmented days than those in work. This was not visible in the overall mean (Figure 5.1.6) since there are fewer respondents in work in June and August 2020 compared to 2016 (cf. Figures 4.1.7 and 6.1.5).

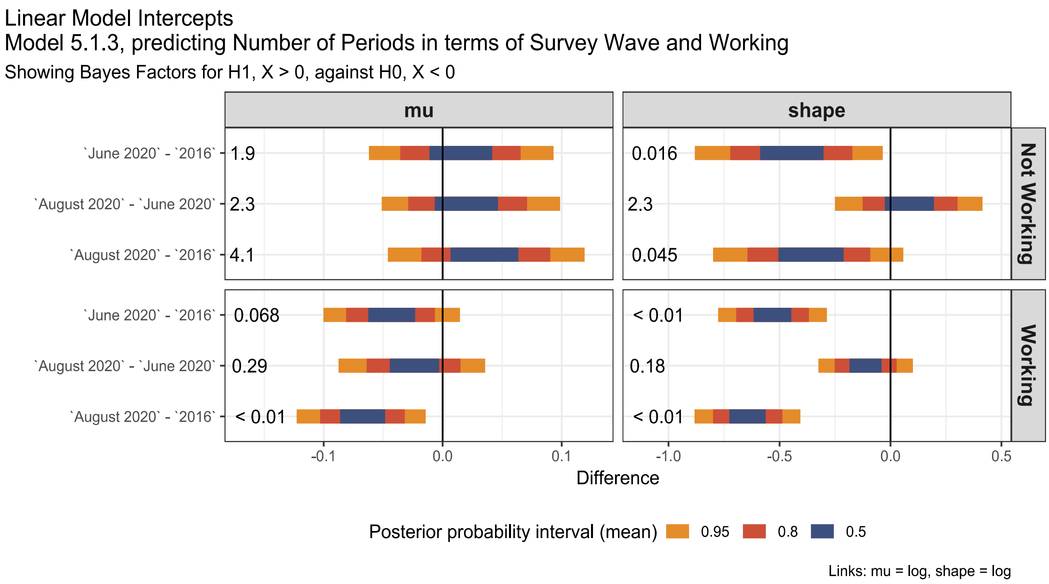

Figure 5.1.8

Figure 5.1.8, meanwhile, shows the results of the same model in terms of the difference between survey waves. It would seem that the cause of the increasing difference in number of periods is caused by those working decreasing the average number of periods on the one hand, and those not working keeping them relatively constant, with weak evidence for a slight increase. This will have contributed to the overall polarisation of the distribution of number of activity periods (Figure 5.1.6), although there is strong evidence that polarisation remains even once being in work is accounted for ('shape' in Figure 5.1.8).

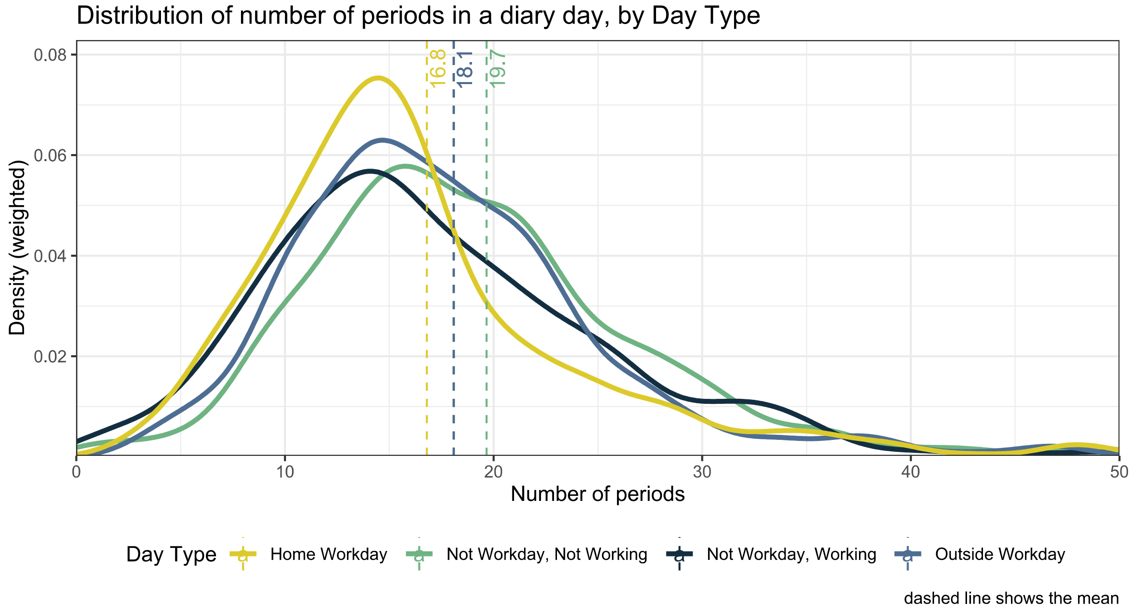

Figure 5.1.9. (The means for 'Outside Workday' and 'Not Workday, Not Working' are identical)

One factor that may explain this result is the shift to working from home, which greatly increased in lockdown both as a percentage of workdays and of all days, something borne out by the figures in this survey (shown above in Figure 4.1.7). Figure 5.1.8 shows that working from home is associated with fewer activity periods per day. Telework therefore leads to workdays having fewer periods per day during lockdown, which is one cause of a decrease in time fragmentation during lockdown, among those working. On the other hand, including working from home as a predictor control only slightly decreases the coefficients in Model 5.1.3, suggesting that it is far from a complete explanation.

This result shows how not all effects on fragmentation are the result of either intensification or the demands of unpaid work. There are also simple effects at work, most notably the fact that days working from home are less fragmented than other work days simply because of the fact that there is no commute, removing two activity periods. This is a reminder that while fragmentation can be linked either to intense time use or the demands of unpaid work, that link depends on the kind of fragmentation in question. While some forms of time fragmentation, such as interruption by housework, are conventionally seen as normatively bad and a source of inequality, other forms such as commuting are normalised.

A second piece of the puzzle comes from returning to the typology of typical daily routines established in the previous section. Certain types of non-workday day, among those that increased the most during lockdown, have either very high or very low numbers of periods. Model 5.1.4 (see Appendix 2) predicts the number of periods in terms of diary day cluster only (controls are not included in order to include the effects of class, sex etc. in the effect of of diary day cluster). The model intercepts for each cluster are shown in Figure 5.1.10. There is a strong link between the type of diary day and time fragmentation, with effects credible at 95% even at the detailed level of individual clusters and the small groups that implies.

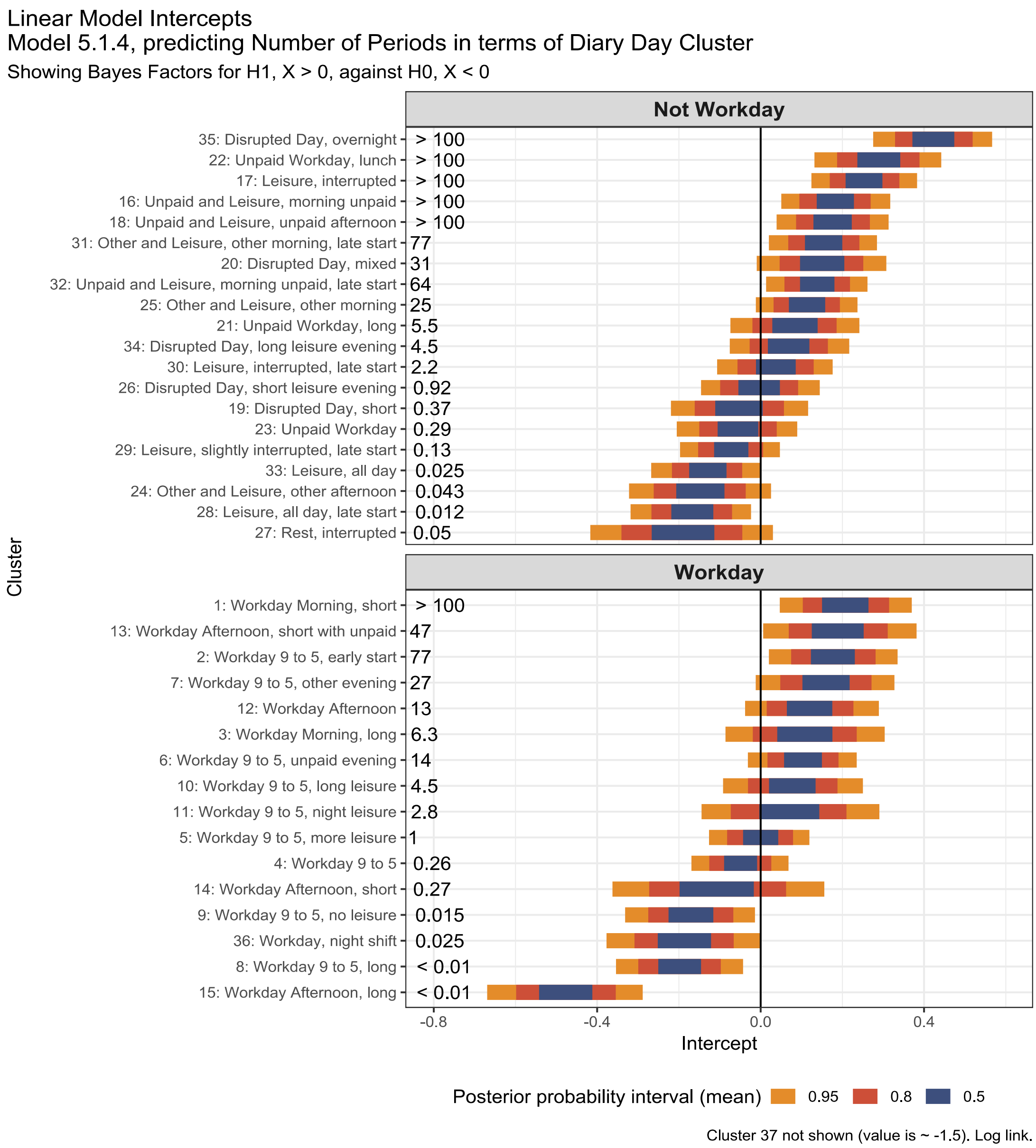

Figure 5.1.10

Starting with non-workdays, Figure 5.1.10 reinforces the implication of Figure 5.1.9 above that non-workdays have more periods, on average, than workdays. But certain typical days, those most typical of lockdown (see section 4), are very highly fragmented. In particular, ‘disrupted days’ are very polarised in the number of activity periods. Those with little leisure time, clusters 20 and 35, are highly fragmented, while those with a large amount of rest (sleep) time such as clusters 26, 34 and 37 are not. The increase in such days over lockdown contributes to the mix of high and low fragmented days. Moreover, other days that were highly typical of June and August 2020 compared to 2016 (see section 4), in particular clusters 17, 22, 25, and 32 appear here more fragmented than average (25 not quite credibly at 95%).

Meanwhile, the fragmenting effect of unpaid work commitments is also visible, supporting the link between unpaid work and fragmentation already discussed, and giving more detail to the overall picture shown above in Figure 5.1.1. The non-workdays in which a significant amount of unpaid work is done are highly fragmented, such as clusters 16, 18 and 22. Moreover, the inequality in days with a large proportion of leisure described in section 4.3, where some (principally men) had uninterrupted leisure days such as cluster 28 and 33, and others had leisure-days with more unpaid work such as cluster 17, have this distinction supported in terms of fragmentation as well (cluster 30 appears to have an intermediate position here). The increase in leisure-dominated days in lockdown accordingly may also contribute to the polarisation in number of periods in a diary day.

Turning to workdays, the results are mainly due to the fact that ‘Paid Work’ time does not contain any information on the sub-periodisation of this time (see section 2.4) and so simply reduces the number of periods in a diary day compared to shorter and part time workdays. This is shown in the fact that clusters 8 and 15, which have the most work time of all and which are particularly characteristic of later survey waves (see section 4.1) have the fewest periods out of the workdays, while short and part-time workdays have most. The latter is at least partly due to the large amount of unpaid work on these part-time work days; in particular, clusters 1 and 13 are visibly disrupted by unpaid work (see Figure 4.1.1), which implies a degree of fragmentation verified by the model here.

Overall, it seems that lockdown caused an increase in days with high levels of fragmentation, and that these were certain non-workdays in which either leisure was disrupted by the need to be available for unpaid work, or daily schedules that were very highly disordered. It also led to an increase in days with little fragmentation, at least in part because of the increase in working from home and consequent lack of commute (for workdays), and also because of the increase in days with long periods of sleep (for non-workdays). The first of these has led to workdays appearing to become less fragmented, and the loss of commute cannot fully explain this. Male-female inequalities in fragmentation appear (from the daily schedules) to be linked to unpaid work, and here lockdown by and large maintained existing inequalities. These were changed principally during the return to work in August 2020, by an increase in time fragmentation for both for women not living with children, and for men with children, respectively increasing and decreasing male-female inequality in this regard.

5.2 Multitasking

The second form of time fragmentation considered here is multitasking. Respondents had the option to indicate a ‘secondary activity’, undertaken at the same time as the first activity entered. Secondary activity is a highly subjective measure: whether a respondent considers that two activities were being carried out simultaneously depends to a great extent on their perception of how time was spent (or indeed, fill out the secondary activity field at all). This has led to a very high proportion of NA values, at around 80%, higher than the ‘gold standard’ methodology of the 2015 survey (Gershuny and Sullivan 2015) where this was 70%, implying perhaps a loss of quality, but not so different as to make the data is unusable. It will however be necessary to examine non-response rates and include them in models, while keeping in mind that a non-response might not imply that unrecorded multitasking took place, since both ‘no secondary activity’ and true non-response are indistinguishable in the data.

Multitasking is measured here by the proportion of 10-minute periods per diary day (out of a total of 144) in which both primary and secondary are filled in, and where primary and secondary activity are not the same. The second criterion deals with a product of the click-and-drag questionnaire, where, for instance a respondent could indicate TV-Childcare-TV on the primary vector, and for the same period continuous Childcare on the secondary vector: here I consider that only the TV-Childcare clash should count as multitasking, with the Childcare-Childcare period simply a product of the ease of clicking and dragging the whole period as childcare on the secondary vector, rather than indicating anything special about that period of Childcare. Using this measure, 13% of time in the dataset counts as multitasking, while 44% of diary days contain at least some multitasking.

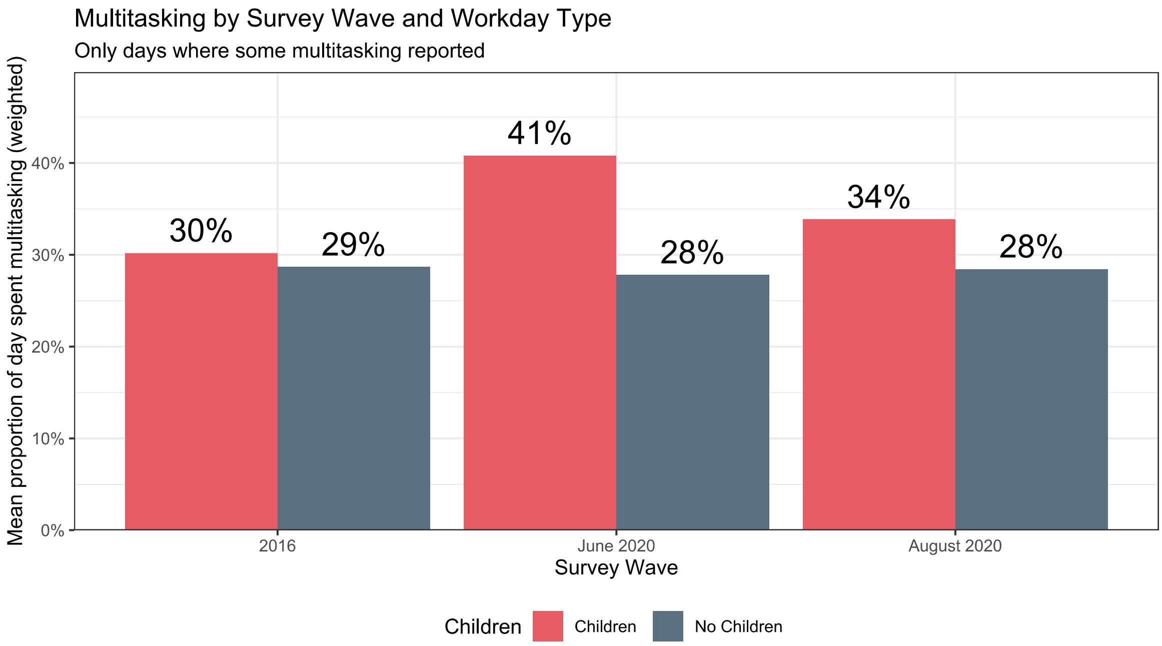

Figure 5.2.1

The impact of having children is far more clear for multitasking than fragmentation, as shown in Figure 5.2.1. Lockdown caused a large increase in multitasking only for respondents with children in June 2020 compared to 2016, which seems to be returning to the previous level by August 2020. This will be the result of increased childcare responsibilities when schools were closed. Model 5.2.1 (see Appendix 2) again fits Gamma-Poisson distribution to the integer values for the number of 10-minutes periods, again controlling for age, sex and class. A zero-inflation term ‘zi’, also modelled in terms of the predictors, is included in order to estimate the probability of non-response.

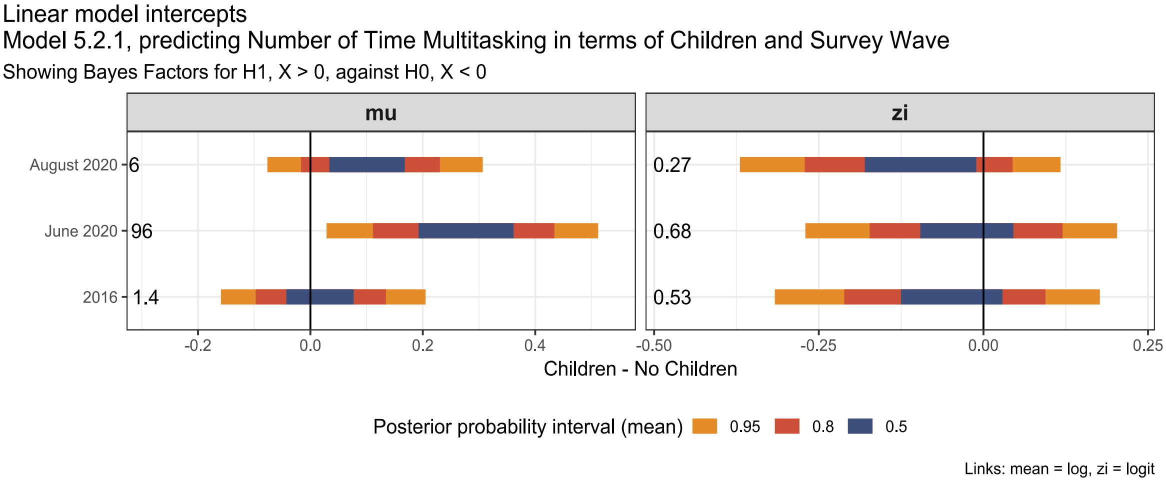

Figure 5.2.2

The principal results are shown in Figure 5.2.2. The zero-inflation term ‘zi’ shows that not reporting multitasking is not related to having children nor survey wave (for this reason, Figure 5.2.1 excludes these values). Meanwhile, only in the wave June 2020 is the difference in intercepts between children and not having children credibly above 0 at 95%; it would seem that lockdown restrictions at this point created a particular situation of high time demand for parents that resulted in childcare being carried out alongside other activities. It should be remembered that the June 2020 data overlaps with school reopening (see section 2.1) and so any effect shown here may be less than that from earlier in lockdown.

Figure 5.2.3 subdivides Figure 5.2.1 between men and women, and shows that increased multitasking resulting from childcare did not apparently create a male-female inequality in this regard. The distributions of multitasking time during lockdown for respondents with children are very similar (and there is no discernible pattern in days without multitasking either). The only large difference in means is that men without children apparently multitasked more in June 2020 (a result not pursued here but perhaps linked to men being more likely to be in work and so work from home). Comparing these results to those for fragmentation above (Figure 5.1.1), male-female inequality is expressed more though fragmentation of time, caused by housework in general rather than specifically childcare. Lockdown childcare, on the other hand, mostly results in multitasking, a burden not in this dataset unequally spread between men and women. (The result is similar to that of the lockdown study of Sevilla et al. (2020, 17-18), although they do find a slight inequality in men's favour in this regard.) A final note on this point is that women with children who work from home apparently have very high levels of multitasking, but that the group is so small in this dataset that no inferences can be drawn.

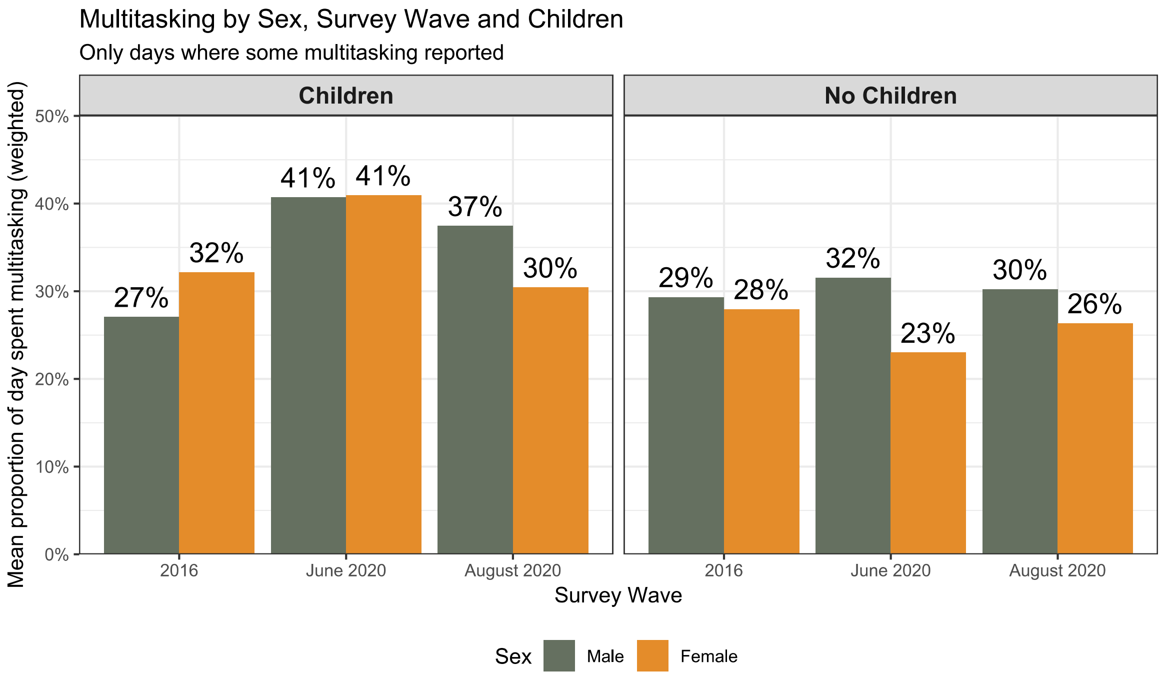

Figure 5.2.3

Turning from the impact of childcare and housework on multitasking to that of work schedules in lockdown, Figure 5.2.4 shows the proportion of time spent multitasking by survey wave: on the left, all diary days, and then the remaining four columns divide this by workday type. While there are some small variations, the main result, mildly surprising in light of the hypotheses advanced in the introduction to this section, is that there is little if any variation in rates of multitasking over the survey waves. The pattern for 'Home Workday', where multitasking appears to decrease in the 2020 survey waves, is not significant due to the small sample size of Home Working in the 2016 wave. The only major pattern is that, across all survey waves, non-workdays when working have higher rates of multitasking than home workdays and workdays when not working, and home workdays than outside workdays.

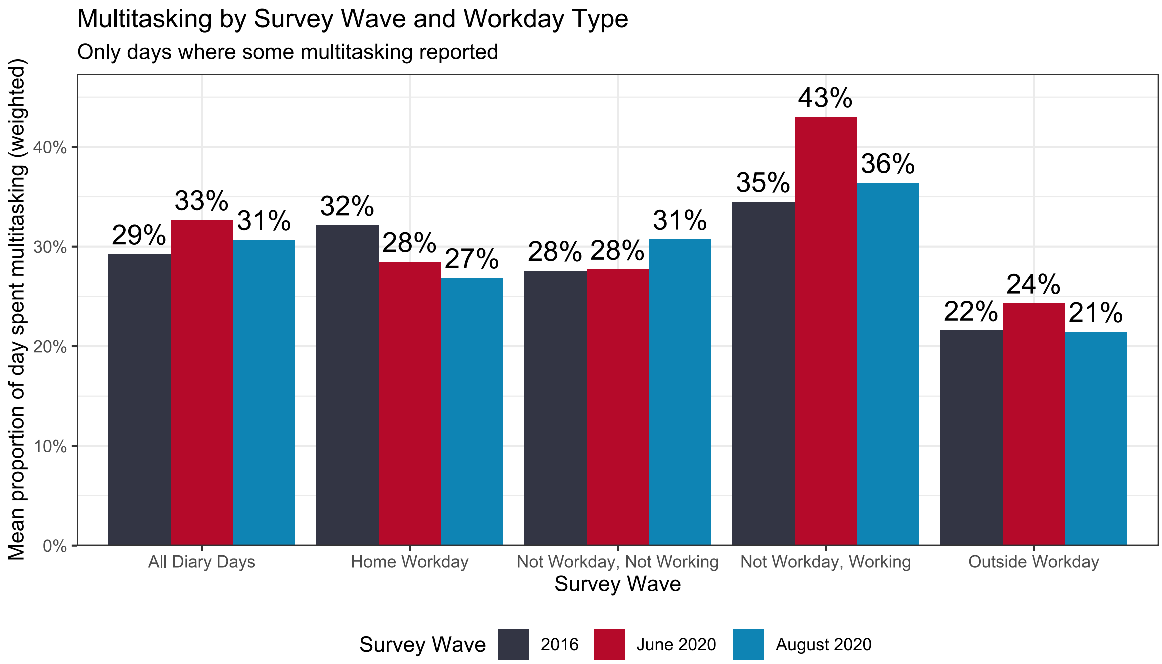

Figure 5.2.4

The evidence for this result is confirmed by Model 5.2.2, which predicts multitasking periods in terms of workday type, controlling for sex, age and class as well as children, and again estimating not only the mean of the distribution with 'mu' but also the non-response rates with a zero-inflated parameter 'zi'. The results of Model 5.2.2 are shown in Figure 5.2.5. While once again (as for Model 5.2.1) there is no evidence that secondary activity non-response ('zi') is linked to workday type, there is strong evidence, with intervals credible at 95%, for a difference between all three kinds of workday.

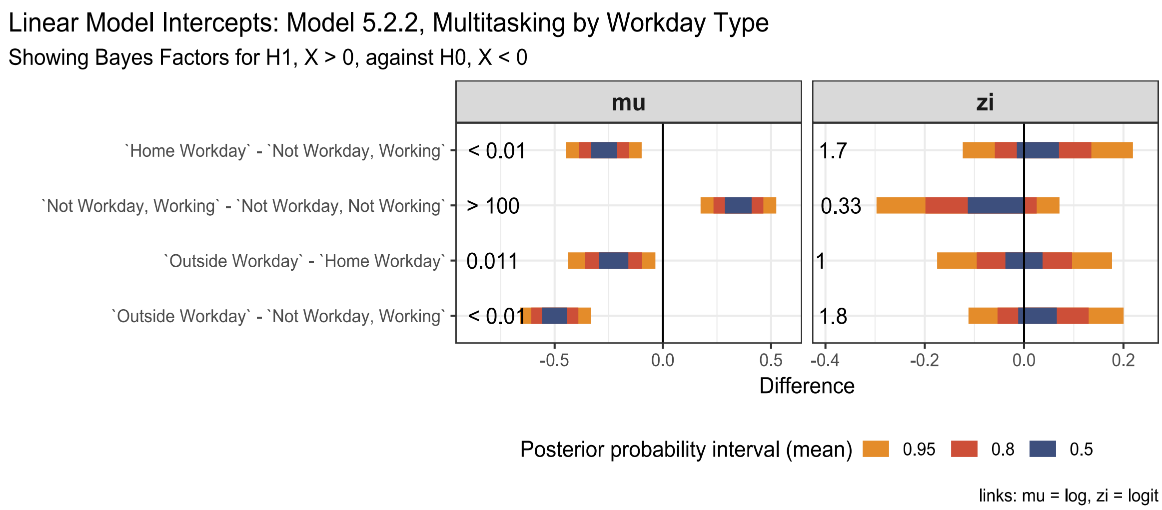

Figure 5.2.5

A second link between multitasking and work behaviour is also apparent in the dataset, when typical daily routines (as described in section 4) are taken into account. In Figure 5.2.6, it can be seen that workdays that follow a ‘9 to 5’ routine (see Figure 4.1.1) have lower levels of multitasking than other workdays. Moreover, the increase in multitasking is of roughly equal size both during and outside work hours (not shown), suggesting that lower multitasking on 9 to 5 workdays is not only a result of greater control of work time, or less working at home, but is linked to the clearer structure of the day as a whole. Model 5.2.3 predicts multitasking in terms of workday type, controlling for age, sex, class and children.

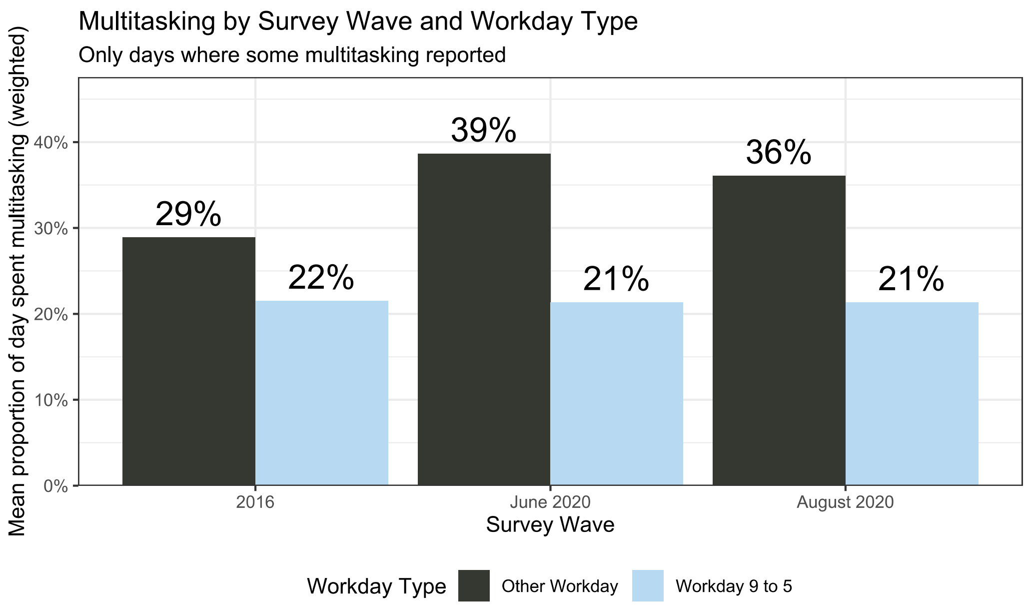

Figure 5.2.6

Figure 5.2.7 shows the main results of Model 5.2.3 and confirms the strength of evidence for this effect, which has an extremely strong Bayes factor, along with a credible interval far from 0. There appears to be very little evidence that non-response (estimated by the ‘zi’ parameter) is linked to the predictor. While Figure 5.2.6 appears to show that the difference between the two workday routines increases in the 2020 survey waves, the relatively small number of workdays in those waves means that the effect is not nearly credible at 95%.

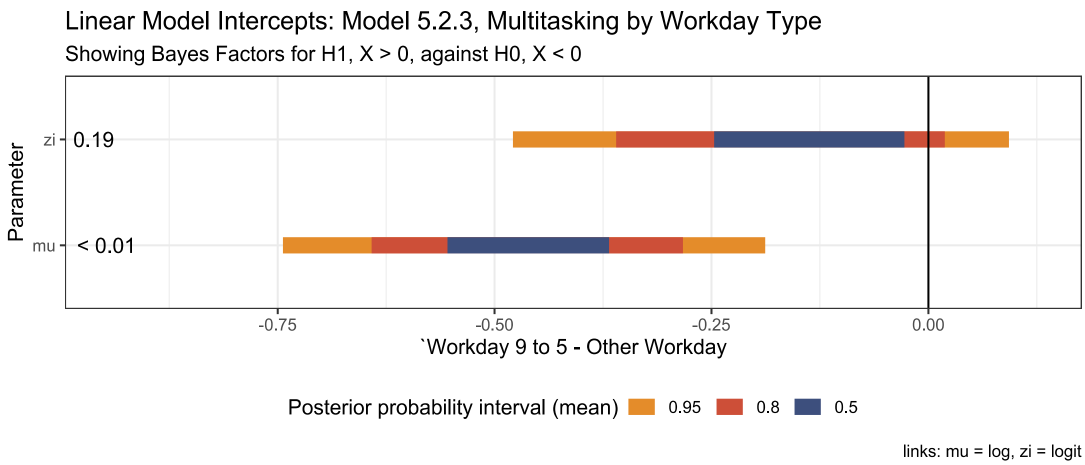

Figure 5.2.7

This result, in fact, leads on to a more generalised link between multitasking and structured daily routine. In this study, the extent to which a daily routine is clearly defined, and can be said to be structured, is linked to the synchronicity of daily rhythms across society, which gives activity-times social meaning. When a respondent's daily routine is in-sync with a common rhythm, each activity 'belongs' to its slot in the day and forms part of a routine whose coherence comes from societal norms of time use. Following such a routine is therefore evidence for organising the day in a meaningful pattern (see section 1.3 and introduction to section 4). Moreover, the average by-timeslot entropy across days in a diary day cluster (as defined in section 4) provides a measure of the synchronicity of routines that can be used to quantify this.

Figure 5.2.8 shows the association between average within-cluster entropy and multitasking. There is no *a priori* relation between the two (as between cluster and fragmentation for example), since multitasking is calculated on the basis of the secondary activity vector, while cluster is only based on the primary activity vector. Nevertheless, Figure 5.2.8 shows a positive correlation. More entropy, and so a less structured daily routine, is associated with higher rates of multitasking. The pattern of Figure 5.2.6 is apparent in the grouping of the 9 to 5 workdays in the bottom left corner: these highly structured days (cf. Figure 4.1.1) have low rates of multitasking. Meanwhile the 'Disrupted Days', with the least structured daily routine (cf. Figure 4.4.1) also have high rates of multitasking, in particular clusters 34 and 35. Other patterns are that the days mixing housework and leisure in a relatively structured manner ('Unpaid and Leisure') have particularly low rates of multitasking, as well as the morning workdays. Days with large blocks of time, such as clusters 27, 33 and 37 (not shown as entropy = 0), reflect a mode of data entry where large amounts of information is entered on the secondary activity vector, making them exceptions to the pattern.

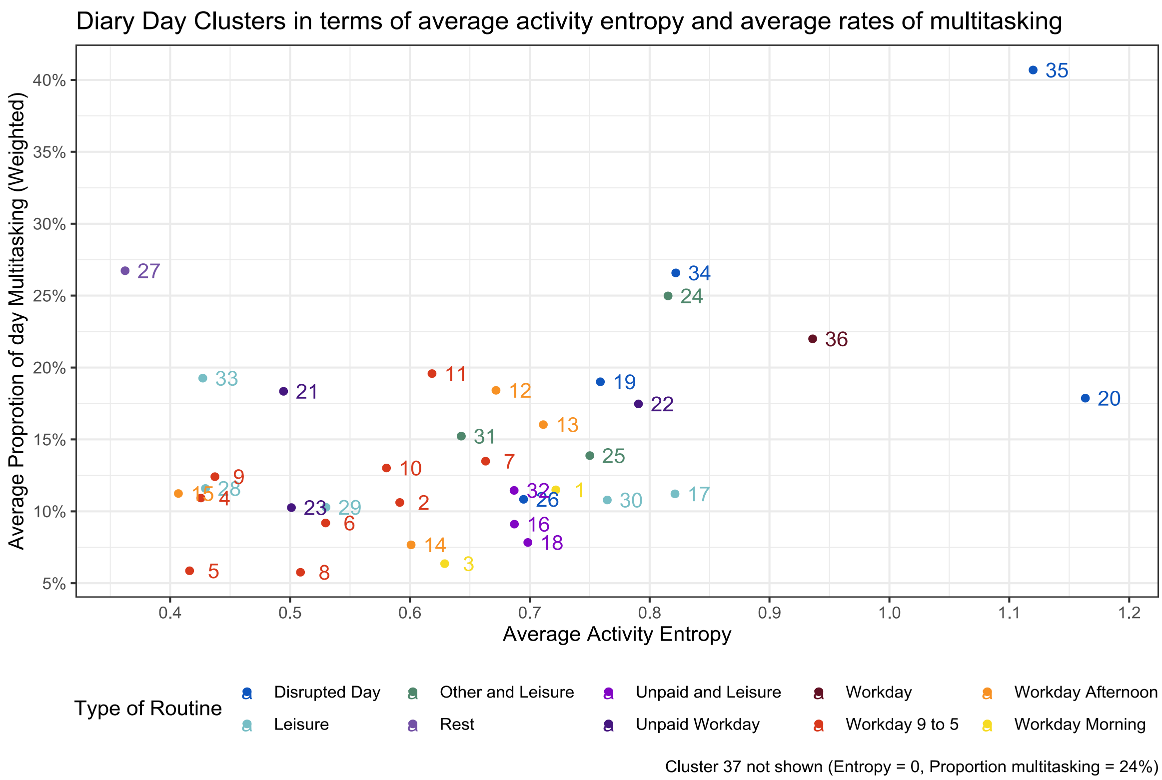

Figure 5.2.8

Model 5.2.4 models daily multitasking (not the by-cluster average shown in Figure 5.2.8) in terms of diary day cluster entropy, as other models in this section using a zero-inflated Gamma-Poisson model, and age, sex, children and class included as controls (which make little difference to the final coefficients).

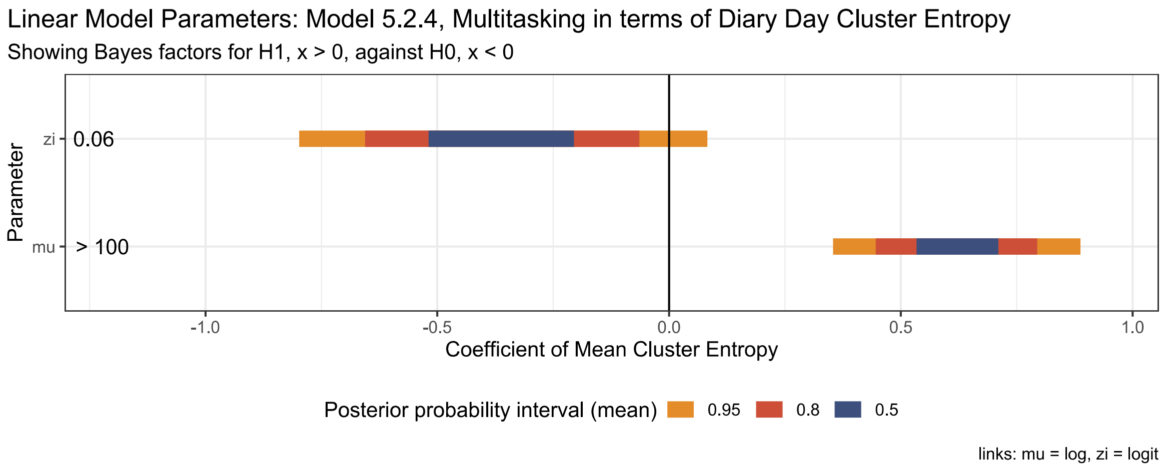

Figure 5.2.9

The results are shown in Figure 5.2.9, which confirms extremely strong evidence for the positive association of entropy and multitasking (the 'mu' parameter, the mean of the distribution). Unlike previous models in this section, there is also moderately strong evidence (although the 95% credible interval overlaps 0) for a negative link between diary day cluster entropy and secondary activity non-response (the 'zi' parameter). This is measuring an aspect of questionnaire response: those giving extremely detailed and so fragmented primary activity vectors are more likely to fill out the secondary activity vector as well.

It would seem, therefore, that not only is multitasking, as measured by the secondary activity vector, the principal way to express disruption to time use caused by the increase childcare responsibilities during the first lockdown, there is also a link between forms of daily routine and multitasking. Non-workdays when working have higher rates of multitasking than home workdays and non-workdays when not-working, and those in turn than outside workdays; 9 to 5 workdays have lower rates of multitasking than non-9 to 5 workdays, and overall less structured daily routines have higher rates of multitasking.

This last result will to some extent reflects questionnaire response, because apparently highly fragmented days may be the result not of different use of time but the result of scrupulously detailed data entry. However, firstly these highly fragmented days, in particular cluster 35, appear strongly patterned by sex and survey wave, suggesting that the cause is not merely data entry but reflects time use in lockdown to some extent. To the extent that this is the case, it implies that more structured daily routines, in which each activity has its socially approved place, lend themselves to concentration on a particular activity in opposition to a more scattered and intense flitting of attention between different activities.

5.3 Multitasking and Mental Health

While there is no clear link between fragmentation and the mental health indicator available in the survey, there is a strong link between mental health and multitasking. Briefly, the mental health indicator used is a combination of eleven questions asking respondents in the 2020 waves to subjectively rate whether aspects of their feelings and behaviour had improved or declined since lockdown began. The subjective questionnaire is not ideal, but it is used as the best available. The indicator is continuous from 0 to 3, where 0 indicates improved mental health in lockdown, 1 indicating no change, 2 indicating worse, and 3 much worse (full specification is given in section 3.3).

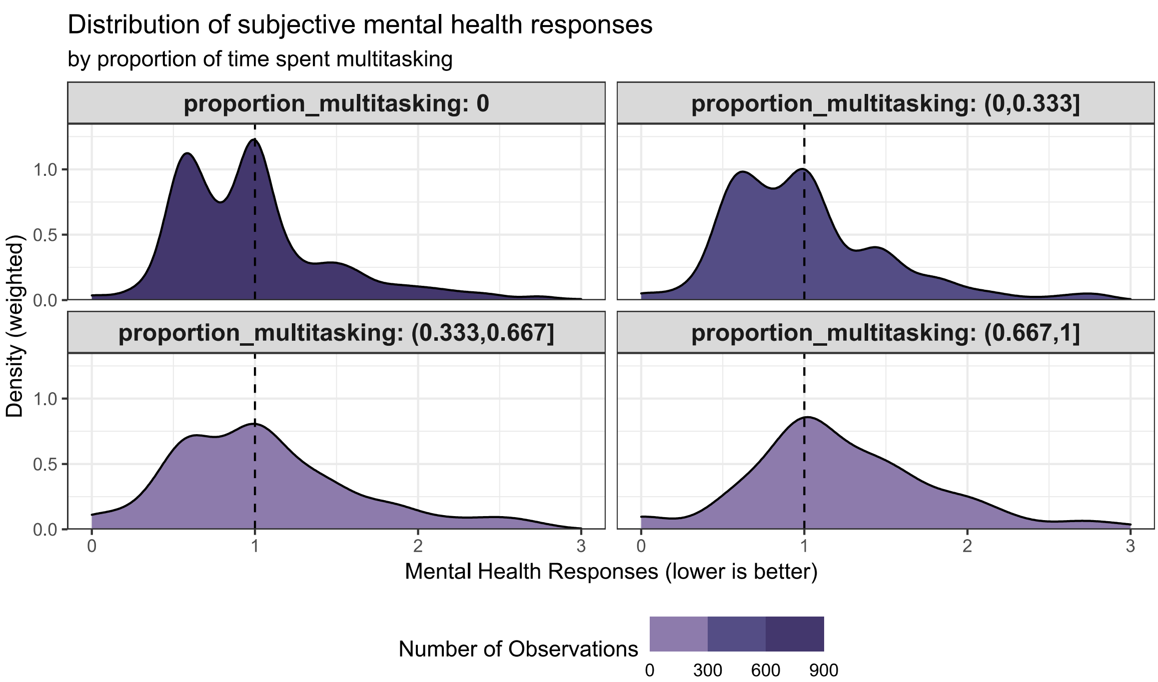

Figure 5.3.1

Figure 5.3.1 shows the distribution of this indicator, according to the proportion of the day spent multitasking. Since 1 indicates no change, better mental health is indicated by more mass to the left of the vertical dashed line, and worse mental health by more mass to the right. It is visually clear that while very few respondents indicated much 'much worse' mental health in any case, many fewer indicated improved mental health and more worse mental health as the proportion of the day spent multitasking increased. Model 5.3.1 confirms this effect, fitting a Gamma distribution, and including sex, children, class and age as controls, as well as work status in lockdown (the model specification is identical to Model 4.6.1 above).

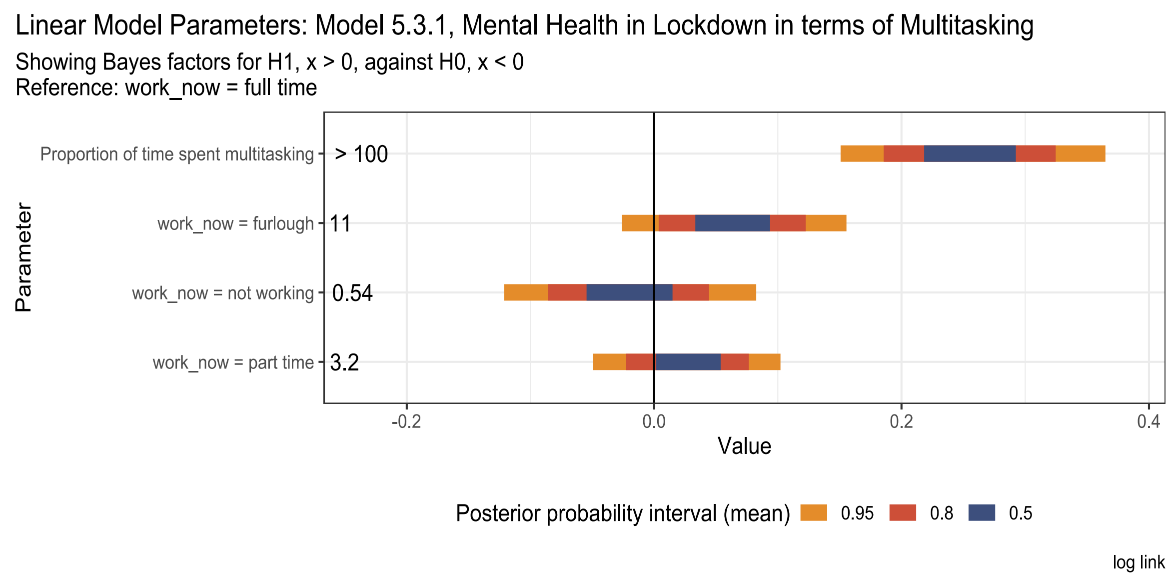

Figure 5.3.2

The results are shown in Figure 5.3.2 (full results are in Appendix B). There is strong evidence that the proportion of time spent multitasking has a negative impact on mental health, credible at well over 95%. The evidence for this effect is much stronger, and the effect much larger, than for the link between furlough and negative mental health. The linear model estimates the difference between no multitasking and a full day multitasking as a positive shift of 1.3 points on the mental health indicator, that is, every one of the eleven questions question changing by, on average, over one answer category to the worse.

5.4 Fragmentation and Multitasking: Overview

It was hypothesised in the introduction to this section that the fragmentation of time use may have increased during lockdown. That increase may have been caused by, firstly, an external demand for availability for housework and childcare increased by presence in the home and the closure of schools, and secondly, a tendency to use time more intensely (Rosa 2013) that may have been given freer rein in increased free time and the *anomie* of time use. The analysis considered both of these causes, looking at time fragmentation both in terms of the number of activity periods, and in terms of the proportion of the day during which two activities were entered on the questionnaire simultaneously. The results for the two measures were quite dissimilar, suggesting that they evaluate different forms of time experience.

In the case of the demands of housework and childcare, it was found that the number of activity periods is linked to male-female inequality in terms of housework, supporting previous research linking male-female inequalities in time fragmentation to the distribution of unpaid labour (Sullivan 1997, Bittman and Wajcman 2000, Sullivan and Gershuny 2018). It seems that the return to work led to two trends in this regard, which appear only in August 2020, after most restrictions had ended: an increase in time fragmentation for women without children, and for men with children. It would seem that men, spending more time at home with a child, find their time more broken up as a result; and it was hypothesised that the strength of the effect in August 2020 is due to the other partner only returning to work (no variable is available to confirm this hypothesis). Meanwhile, it seems that women see their time as more fragmented by housework, and not by childcare, which is principally entered in the form of a simultaneous activity. The closure of schools in lockdown appears to have led to a large increase in multitasking (simultaneous activities) in June 2020 only, for households with children only. There was no evidence that this is unevenly distributed between men and women. More detailed analysis of precisely which activities were ‘multitasked’ or caused fragmentation was not possible with the size of the dataset available.

Turning to the link between stopping work, working from home, increased free time and time fragmentation in lockdown, once again quite different patterns were found for the two different indicators. The number of periods in the day did not increase overall, but became more polarised, as there was an increase in both highly disordered days with many periods, and days where a large portion of the day was spent asleep. This behaviour would have been enabled by the *anomie* of lockdown, which allowed days with less routine. Moreover, there was a decrease in activity periods on workdays, which appeared partially but not entirely due to the shift to working from home and the consequent loss of a commute. When multitasking is considered, it was found that non-workdays when working have higher rates of multitasking than home workdays and workdays when not working, and home workdays than outside workdays. While there is a slight indication this led to an increase in overall multitasking in lockdown, the effect is too small for confidence.

Moreover, a link was found between the extent to which a daily routine is in-sync with other members of society (both in terms of 'standard workday', and the scheduling of leisure and unpaid work on non-workdays) and the amount of multitasking. It might be inferred from the latter result that disorganisation of daily schedule is linked to a certain experience of time as filled with simultaneous activities, which could be seen as 'hyperactivity', using time more intensely, or alternatively as being constantly interrupted (which Han (2015) argues are two sides of the same coin). Multitasking is furthermore linked to (subjectively assessed) poor mental health in lockdown, even when living with children and stopping work are included as controls. While the indicator is unfortunately only subjective, there is therefore some evidence that, quite apart from the increased multitasking load associated with living with children, this scattered or interrupted experience of time, flitting between different activities, has negative mental health effects – a result which supports Han's theorisation of 'burnout' (2015). The result is parallel to the link between poor (subjective) mental health in lockdown and less structured daily routine demonstrated above in section 4.6.

6 Engagement in Leisure Activities

Lockdown time was not only more free from obligations than it had been, but as argued above (in section 1.1), it was also free from social norms that had governed appropriate leisure activities. Leisure activities to large extent get their meaning and purpose as ‘what to do when not working’; when there was no work to go to and come back from, the question of what to do when not working was suddenly more open than before. In this way free time during lockdown resembled the ‘anomic leisure’ (Gunter and Gunter 1980) of the pre-lockdown unemployed. While section 4.3 considered the place of leisure activities as a whole in daily routine, this section looks at the interior of the ‘block’ of leisure activity examined there, in order to look at how leisure practices may have changed during lockdown. The style of leisure behaviour is considered separately from the amount of leisure time available.

Leisure activities are cultural practices, and cultural behaviour is shaped by education as part of the process of reproducing society’s class structure (see section 1.3). The analysis of this section is accordingly carried out in terms of educational level, which reveals differential responses to lockdown in terms of leisure practices. Because of the limitations of sample size, educational level is used as simply a binary category, (university) ‘Degree’ and ‘No Degree’ (details in section 3.3 and Appendix A). It should also be kept in mind that the survey sample is severely deficient in the number of people without GCSEs. On the assumption that these people are the most emblematic of the effect of little education, that will lead to the difference between the Degree and No Degree categories being underestimated.

Two measures are used. Firstly, section 6.1 looks at the number of different leisure activities in a diary day (voracity). This has been the subject of some previous research: Southerton (2006) finds that voracity increases with educational level, while Sullivan and Katz-Gerro (2007) link it to social class and the omnivorous thesis of Peterson (1992). While there has been much debate over Peterson’s thesis, eclecticism in cultural activities, of which voracity is the time-use equivalent, does seem to be indicator of educational level and social class (Coulangeon 2010). It can moreover be seen theoretically as an indicator of performing leisure activities in order to accumulate of cultural capital, for the purposes of social competition (cf. section 1.3).

Secondly, an attempt is made to examine the content of leisure activities in section 6.2. Unfortunately, the limited size of the dataset means that a detailed examination of many forms of leisure activity is not possible; however, conclusions can be drawn concerning consumption of electronic media, grouped under the activity code ‘Watching TV, Video, DVD, Music’. Since consumption of electronic media is typical of all social groups, rather than the higher educated (e.g Robette and Roueff 2014; Jonchery and Lombardo 2020, p.13), I suggest here that the proportion of leisure activity time spent in this activity code can also be understood as a second indicator that differentiates the leisure practices between educational levels. While of course related to voracity, since a greater proportion of time in a single activity code tends to imply fewer activity codes overall, it is not identical and the results are quite different.

Several different perspectives on leisure activity behaviour would lead us to expect different reactions to the *anomie* of lockdown. It might, firstly, be hypothesised that the decrease in social interaction decreased the pressure to engage in high-status forms of leisure activity as part of social competition. On the other hand, the voracity and variety of leisure activities may have increased, either as the increased uncertainty over future life prospects led to people accumulating cultural capital, or as the lack of possible activities in the day led people to seek diversion or self-realisation in new leisure activities. Moreover, the change in work and childcare obligations in lockdown will have led to very different experiences and degrees of *anomie,* and the fact of working, or not, during lockdown, may have led to different patterns of leisure activities.

6.1 Voracity

Voracity is defined here as the number of different leisure activities in the day, as measured in terms of the survey’s activity codes, of which twelve are defined as leisure activities here (cf. Figure 6.2.1 below).

When looking at voracity in lockdown, a first consideration is that lockdown reduced the number of possible leisure activities in the day, by restricting some, such as dog walking, and forbidding others, such as trips to the cinema. In the survey, such outdoor activities refer to five of the twelve codes considered as 'leisure' here. It might therefore be expected that voracity as measured by the dataset's activity codes would decrease in lockdown. Figure 6.2.1 shows the average number of leisure activities per day, divided into leisure activities that must take place outside, and those that can take place inside.

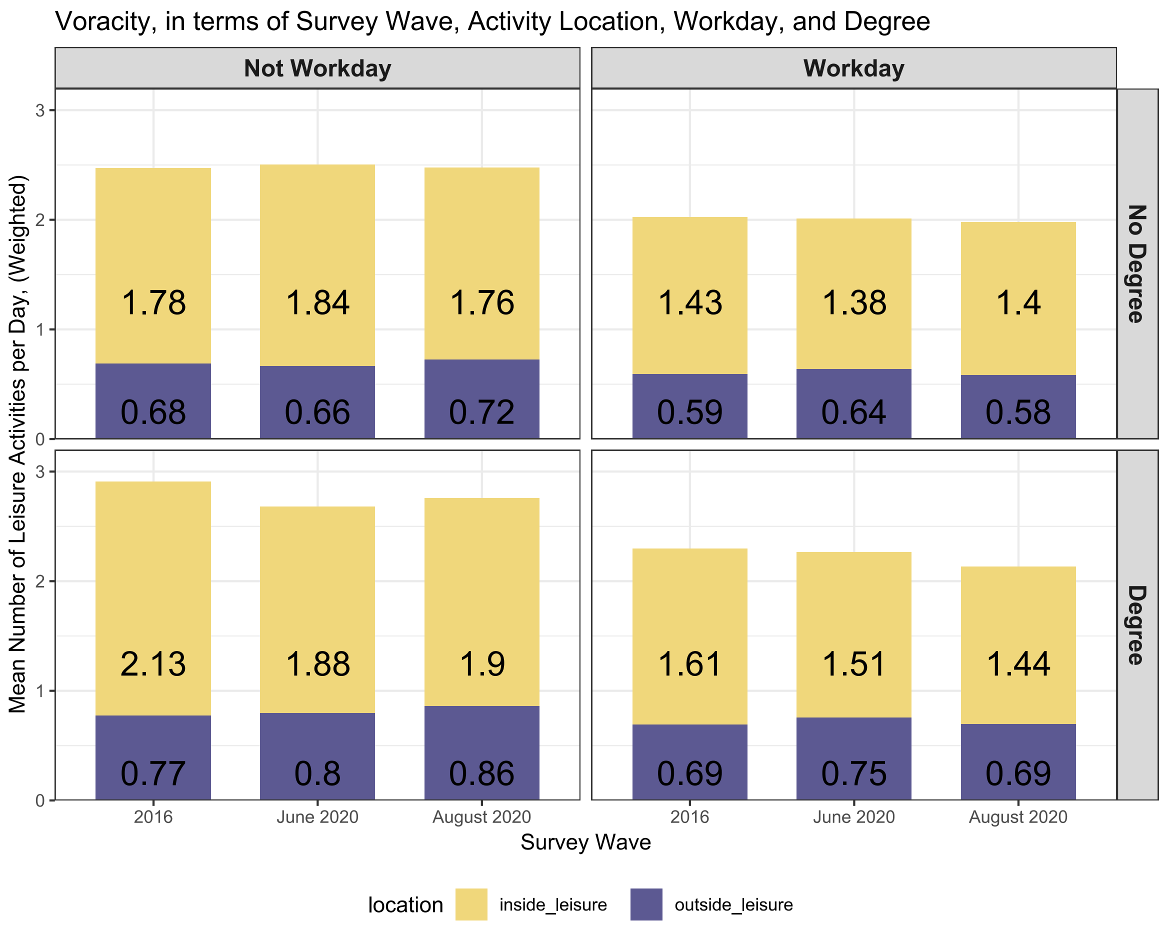

Figure 6.1.1

In appears, however, in Figure 6.1.1 that outside leisure activities do not decrease into lockdown, at least by no significant amount. This is probably because the average number of outside leisure activities per day in the 2016 survey wave was below 1, and so sufficiently low for lockdown restrictions to have not significantly impacted the rate; those impossible (such as going to the cinema) may have been replaced by others (such as going for a run).

Figure 6.1.1 further shows that overall voracity was relatively constant over lockdown. At least measured using the activity codes in the survey, it seems that there was no explosion in the variety of leisure pastimes during lockdown. Degree holders are more voracious than non-degree holders over all survey waves. Moreover, Degree holders' voracity as regards inside leisure activities on non-workdays (but not outside leisure activities) decreased from 2016 into June 2020, before rebounding slightly into August 2020. Their voracity on workdays also decreased, but much more slightly. Non-degree holders do not show this decrease, leading to a narrowing of the gap between educational levels.

A second consideration when evaluating voracity is whether to take into account the quantity of leisure time available during the day. If this is not taken into account, then days with more leisure time naturally tend to include more different leisure activities: this is apparent in Figure 6.1.1, where 'workdays' have fewer leisure activities than 'non workdays' (coding defined in section 3.3), because work takes up a large portion of the day which is not available to leisure activities. The object of this section is to evaluate the style of leisure practices, rather than the effect of changing work and unpaid work obligations on the amount of leisure time available in lockdown. Therefore, it is appropriate to control for the amount of leisure time in the diary day.

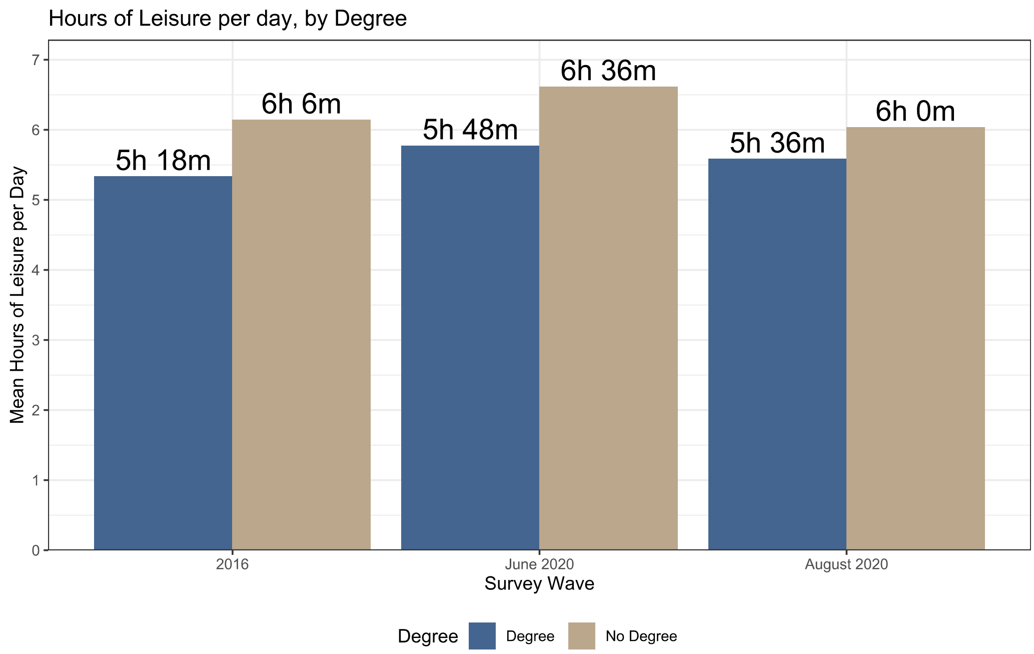

Figure 6.1.2

But here there is a further complication: respondents without a degree spent more time in leisure activities on the whole, on both workdays and not workdays, than those without. Figure 6.1.2 shows that they had an average of over half an hour more in each wave. It appears, in fact, that the variables of total time in leisure activities on the one hand, and having a degree (as opposed to not) on the other, are in a masking relationship when predicting voracity. Degree holding in itself is positively associated with voracity, but degree holders have less time in leisure activities, which partly 'masks' the effect. To confirm this, three models (Models 6.1.1, 6.1.2, 6.1.3 – see Appendix B) were fitted, predicting voracity in terms of degree, then leisure time, then both. Voracity was modelled by fitting a Poisson distribution to one less than the number of leisure activities, producing excellent model fit. 174 diaries were excluded because they contained no leisure activities.

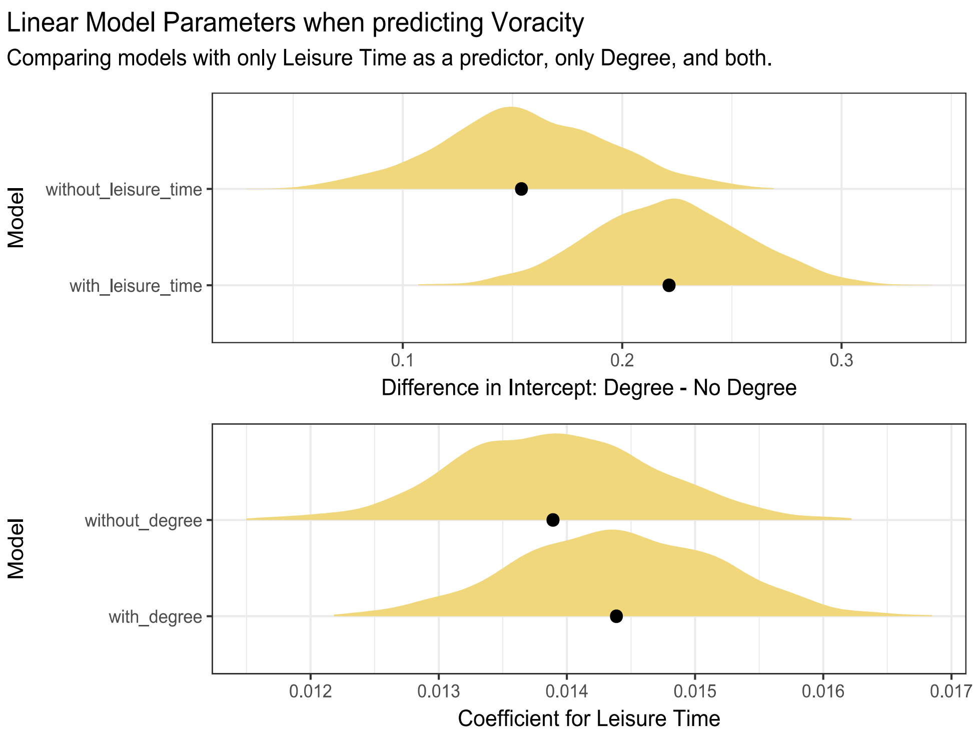

Figure 6.1.3

Figure 6.1.3 confirms the masking effect. The top panel shows the difference in linear model intercept between degree holders and non-degree holders in two models, one where degree is the only predictor, the other where leisure time is included as a control (the black dot shows the mean of the distribution). In the latter, the effect of degree increases. The bottom panel is the same, but looking at the coefficient of leisure time rather than degree: this also increases when degree is included as a predictor. Leisure time is accordingly included as a control when estimating the relationship between degree, survey wave and voracity.

This is done by Model 6.1.4 (see Appendix B) which includes the further controls of age and sex as well as whether the day is a workday, while predicting voracity in terms of the interaction of degree and survey wave, once more fitting a Poisson distribution to one less than the number of leisure activities performed. 17 cases where work status was unknown were excluded from the model, as well as 174 cases where no leisure activities were performed.

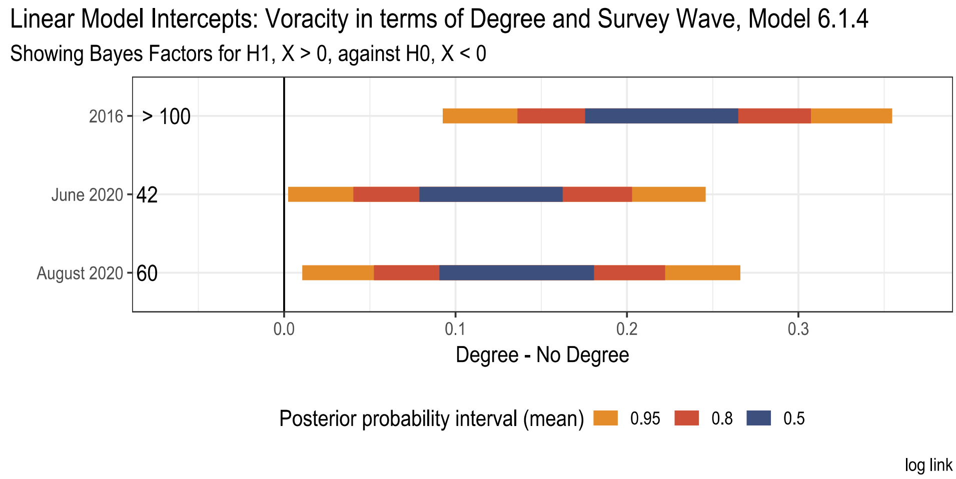

Figure 6.1.4

Figure 6.1.4 shows the results of Model 6.1.4 in terms of the difference between degree holders and non-degree holders (full results are in Appendix B), confirming that there is strong evidence for the implication of Figure 6.1.1 that having a university degree is associated with higher voracity in all three survey waves. This confirms the past results of Southerton (2006) and Sullivan and Katz-Gerro (2007) for 2016 and the first UK lockdown. However, there is a second pattern: it also appears that the gap between degree holders and non-degree holders has narrowed over lockdown.

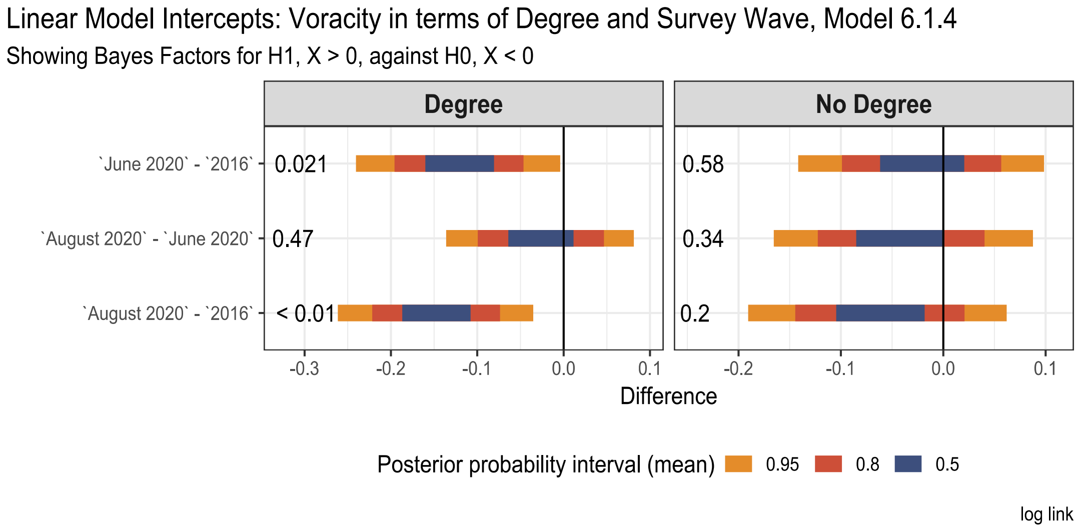

Figure 6.1.5

How to explain this effect? Figure 6.1.5 looks at the survey differences in the intercepts in Model 6.1.4. This shows that the change in voracity between survey waves took place among degree holders rather than non-degree holders. For degree holders there is strong evidence for a decline in voracity in June 2020 compared to 2016, and extremely strong evidence for August 2020 compared to 2016 when there has been a slight further decline in the data (cf. Figure 6.1.1). Meanwhile, there is only weak evidence (Bayes factor = 0.2), and a credible interval easily overlapping 0 at 95%, for those without a degree over the same period.

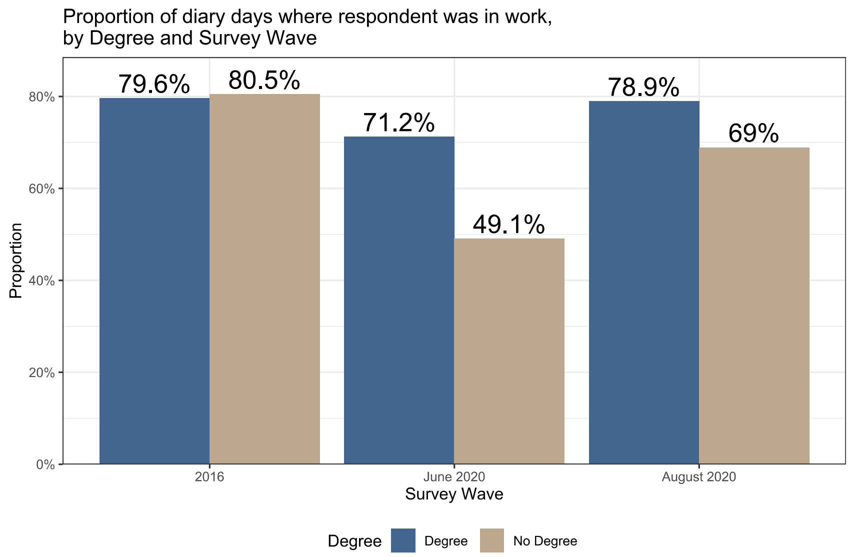

Figure 6.1.6

Another possible cause is the differential rates of stopping work in lockdown, shown in Figure 6.1.6: respondents without a degree were far more likely to be not working in June 2020 compared to not be working in 2016, with a partial closing of the gap in August. While the amount of leisure time available (less on workdays) is already accounted for by including it as a control, it has been underlined (in section 1.1) that the experience of *anomie* in lockdown was very different according to whether someone remained working. However, in order to check for this effect, Model 6.1.4 already included this as a control, making hardly any difference to the results.

While rates of stopping work are not the cause of the smaller difference in voracity between degree holders and non-degree holders, stopping work does appear to have had a different effect on rates of voracity. Model 6.1.5 re-fits model 6.1.4, this time including as an interaction variable the fact of being in work, or not, during lockdown. The smaller group sizes mean that few effects are credible at 95%, but the results are worth briefly examining in order to get an indication of which groups are driving the changes observed in the model above.

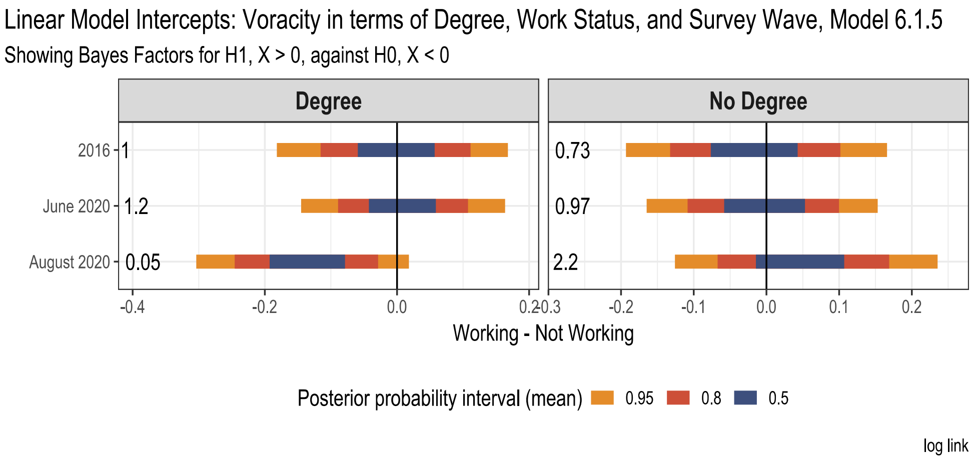

Figure 6.1.7

The main results in terms of the difference between those working and those not are shown in Figure 6.1.7 (full results are again in Appendix B). It can be seen that both those working and those not responded to lockdown in similar ways in June 2020: there is no evidence that the decrease in the voracity of degree holders was greater among those not working during lockdown. In August 2020, however, there is strong evidence that degree holders not working were more voracious than those who had returned to work.

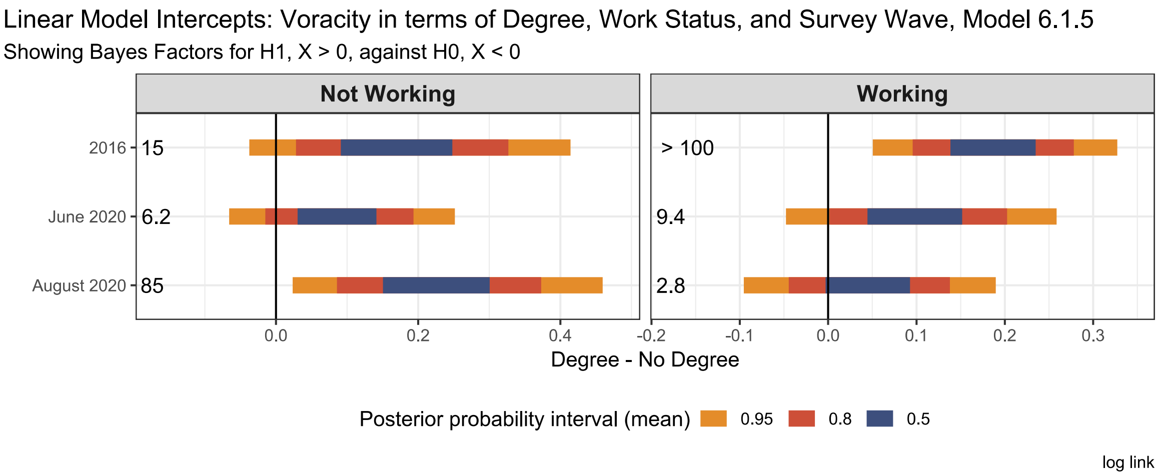

Figure 6.1.8

Figure 6.1.8 presents the same model's results in terms of the difference between degree holders and those without. It can be seen that in 2016 there is much better evidence that the difference between degree holders and those without is due to those in work. However, in August 2020 the effect of Figure 6.1.7, where it is degree holders out of work who become more voracious, is seen in a different way. The pattern has inverted, and there is much better evidence that the difference in voracity is found among those out of work. Figure 6.1.7 shows that this is due to changes in the behaviour of degree holders.

It would seem therefore that in 2016 differences in rates of leisure voracity reflect the ‘harried leisure class’ (Gershuny 2005): degree holders in work do more leisure activities per unit of leisure time. However, in lockdown degree holders decreased the voracity of their leisure consumption (Figure 6.1.6), and this trend continued even as many returned to work in August 2020. This is perhaps due to the lessening of social interaction as a venue for social competition, or the continuation of lockdown leisure habits (cf. Section 1.3). By contrast, it was degree holders who remained out of work in August 2020 who increased their leisure consumption. A possible interpretation would be that those who remained out of work increased their leisure consumption to accumulate cultural capital, putting their time to ‘good use’, while those returning to work felt no such pressure. The lack of change in those without a degree indicates that the voracity of leisure consumption in this group was not affected by lockdown.

6.2 Proportion of Leisure Time Spent in Consumption of Electronic Media

Perhaps the most obvious way to analyse leisure activities is to look qualitatively the activities engaged in. However, the construction of an indicator is complicated in two ways. Firstly, there are only a limited number of activity codes considered here as leisure in the dataset, which are necessarily very broad and fall far short of a detailed qualitative assessment of leisure activity. Secondly, many of the activity codes appear in only a small proportion of diary days. When only a few dozen diary days engage in an activity, it scarcely possible to draw any conclusions about how its rate may vary over survey waves or between demographic groups.

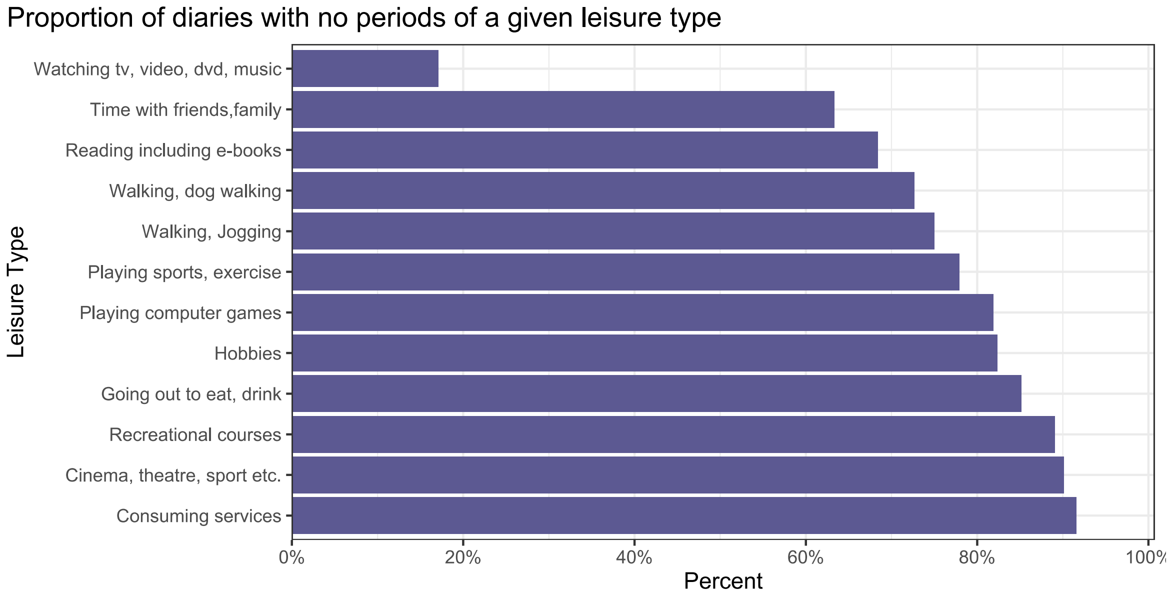

Figure 6.2.1

Figure 6.2.1 shows the activity codes considered as leisure activities, as well as the proportion of diary days without any period of each activity. It seems that the second problem raised in the preceding paragraph, the low rates of certain leisure activities, will be severe, since only one category, 'Watching TV, Video, DVD, Music', is found in over half of diary days.

The approach adopted here attempts to take care of both problems, in a way that is necessarily somewhat broad-brush. Of the activity codes available, one – 'Watching TV, Video, DVD, Music', that is, the consumption of electronic media, – is found in over 80% of diary days, and covers 50% of all diary day periods assigned to any kind of leisure. It is therefore a measure sufficiently varied across all diary days to be analysable given the sample size available. In order to consider patterns of leisure time behaviour separately from constraints on the time available for leisure (cf. section 6.1), it is not the amount of time spent in the category 'Watching TV, Video, DVD, Music' that is considered, but the proportion of the total time on leisure activities devoted to it (on the primary activity vector), for each diary day. The indicator is therefore the proportion of leisure time spent in media consumption, a continuous measure from 0 to 1.

Figure 6.2.2 shows the distribution of the proportion of leisure activity time spent on consumption of electronic media, grouped by degree and survey wave and shown as a histogram. The shape of the distribution is worth a remark. The central bump is the distribution of the proportions; shifted to the left indicates less, to the right more, and it's flatness indicates the amount of spread. However, many diary days have no periods of consumption of electronic media, or spend all of their leisure time in it, as can be seen from the two tall bars at either end of the distribution.

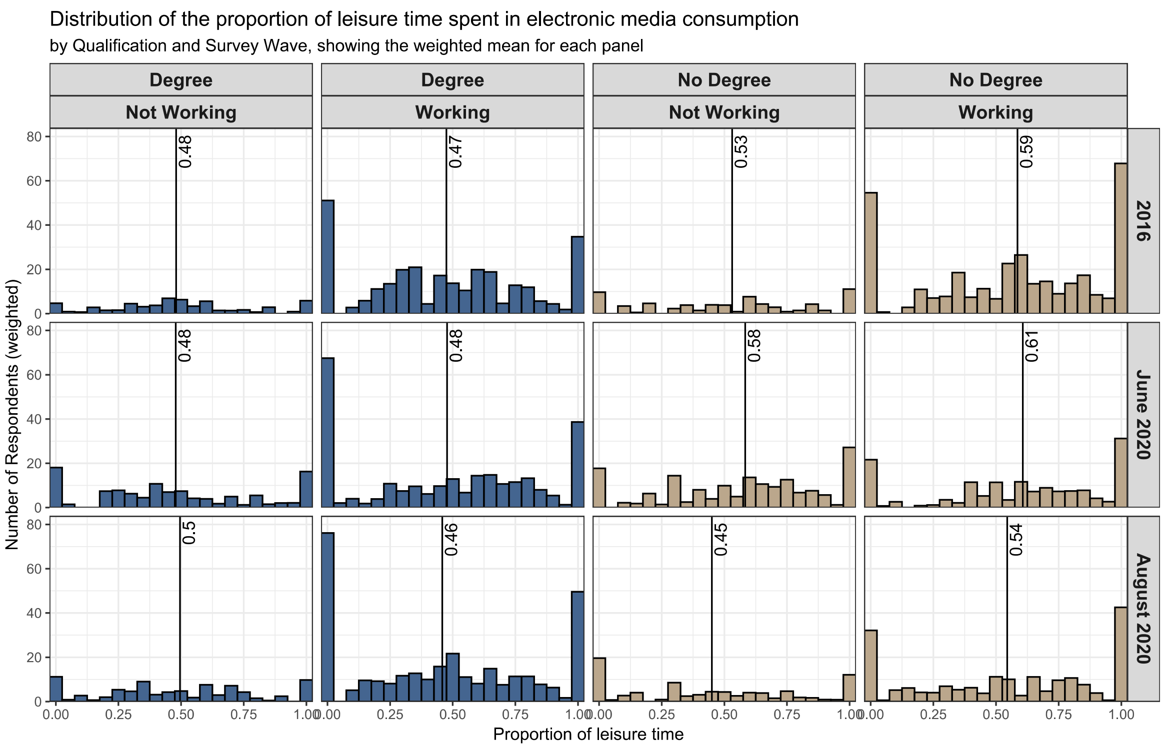

Figure 6.2.2

The results of Figure 6.2.2 are, firstly, that respondents without a degree spend a higher proportion of leisure activities in media consumption, on average about 60% as opposed to around 50% for degree holders. This is reflected not only in the spread of respondents with proportions between 0 and 1, but also in the numbers of respondents who spend no or all leisure time in media consumption. However, in August 2020, those without a degree decreased their consumption of media leisure, bringing it into line with degree holders.

Model 6.2.1 estimates the size of the effect in the population of reference, predicting the proportion of leisure media consumption in terms of the interaction of degree and survey wave, controlling for age and sex, as well as whether the day is a workday. The model fits a Gaussian distribution, which while it does not provide a close fit to the distribution of the data, provides a simple estimation of the change in average without making any additional assumptions. 17 cases where work status was unknown were excluded from the model, as well as the 174 cases with no leisure activities.

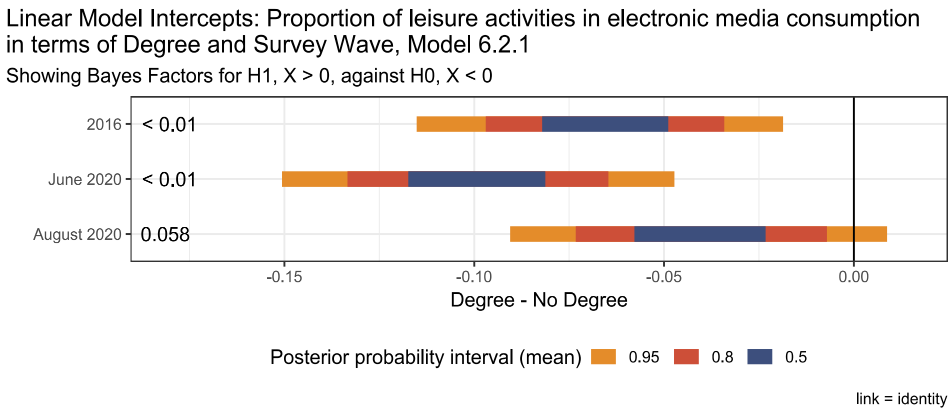

Figure 6.2.3

The main results in terms of the difference between degree holders and those without are shown in Figure 6.2.3 (full results in Appendix B). It can be seen that there is extremely strong evidence, with 0 outside the 95% credible interval, that those without a degree spent a greater proportion of leisure time consuming electronic media in 2016 and June 2020, as well as strong evidence for August 2020. This suggests that this indicator is reflective of differences between educational levels and so social classes in forms of leisure activity; Degree holders spend a smaller proportion of leisure time in electronic media consumption. Moreover, since ‘workday’ is included as a control (making almost no difference to the results), the change in difference between survey waves is not directly caused by the higher rate of stopping work among non-degree holders (cf. Figure 6.1.5).

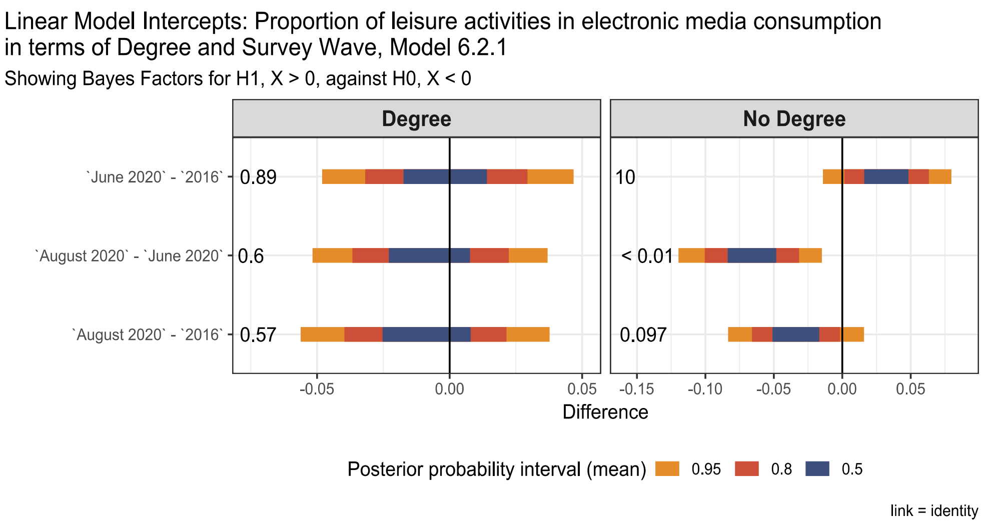

Figure 6.2.4

Was it degree holders or not degree holders that drove the observed changes? Figure 6.2.4 shows the results of Model 6.2.1 in terms of the difference between survey waves. This shows that it is not degree holders who changed over lockdown (as in section 6.1), but non-degree holders, for whom there is moderate evidence for an increase in June 2020 compared to 2016, and extremely strong evidence for a decrease in August 2020 compared to June 2020.

Further detail is brought by Model 6.2.2, which adds work status as an interaction predictor, in order to see whether there were differences in reaction to lockdown between those working and those who had stopped. Figure 6.2.5 shows the difference in intercept between these two groups. There is no evidence that the change observed in non-degree holders in June 2020 takes place more among those working or those not; however, there is moderately strong evidence (if not credible at 95%) that it is those working who spend more of their leisure time consuming electronic media – and so who are *least* responsible for the observed decrease in August 2020 compared to June shown in Figure 6.2.4.

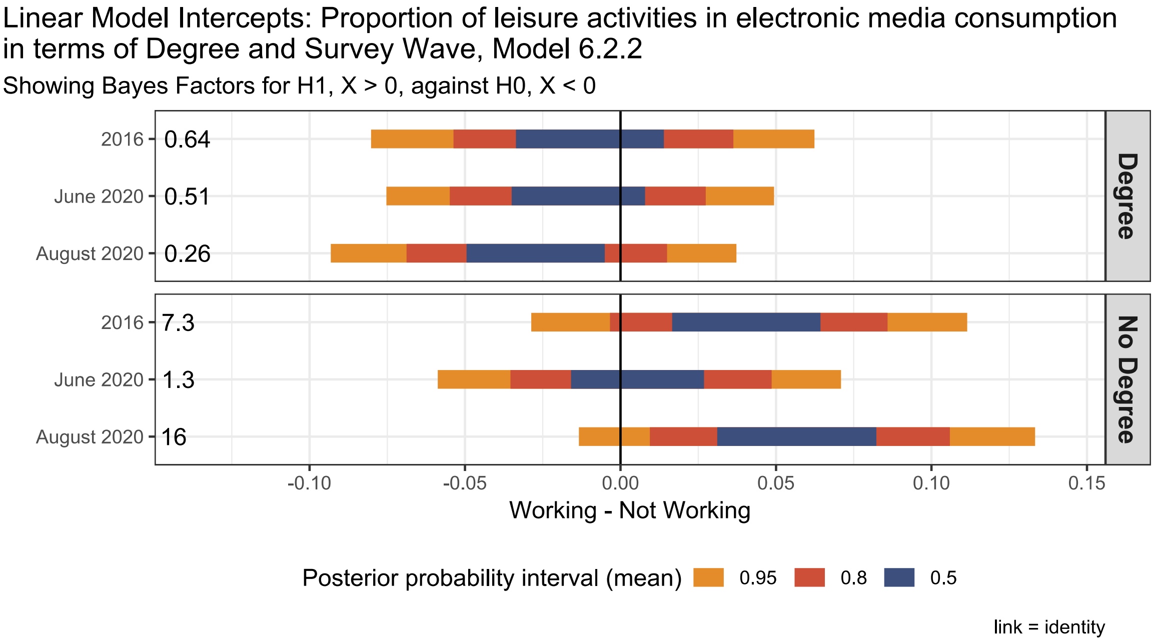

Figure 6.2.5

Figure 6.2.6 shows the results of the same model in terms of the difference between educational levels: it is among those working that there is the strongest evidence for a difference in leisure practices, which is maintained during lockdown. The change in the difference in leisure practices shown in Figure 6.2.3, a decrease in gap during lockdown before a re-establishing of pre-lockdown inequality are to be found among those not working.

Taking the results of Models 6.2.1 and 6.2.2 together, in all survey waves degree holders spent a higher proportion of leisure time in the consumption of electronic media than non-degree holders, supporting the relation between this indicator and the patterning of leisure activity by educational level. In June 2020, non-degree holders, both in work and not working, increased this proportion, widening the gap. However in August 2020 non-degree holders who were not working in particular greatly decreased the proportion of leisure time spent in consuming electronic media, leading to a closing of the gap compared to June 2020 and 2016. Since television consumption among the less qualified is still strongly related to family time together (Masclet 2018), it is tempting to link this pattern to the result of section 8, that working-class families spent more time together during lockdown. On the other hand, the large decrease in August 2020 could perhaps be explained by seeing the consumption of electronic media as an activity that, compared to other leisure activities, is considered less 'self-improving' in the perspective of Binkley (2009) and Petersen (2020, ch. 8). While this view is heavily generalising and needs support by detailed qualitative research – there are many different ways to approach watching TV, for instance – it does offer a plausible explanation of the effect observed.

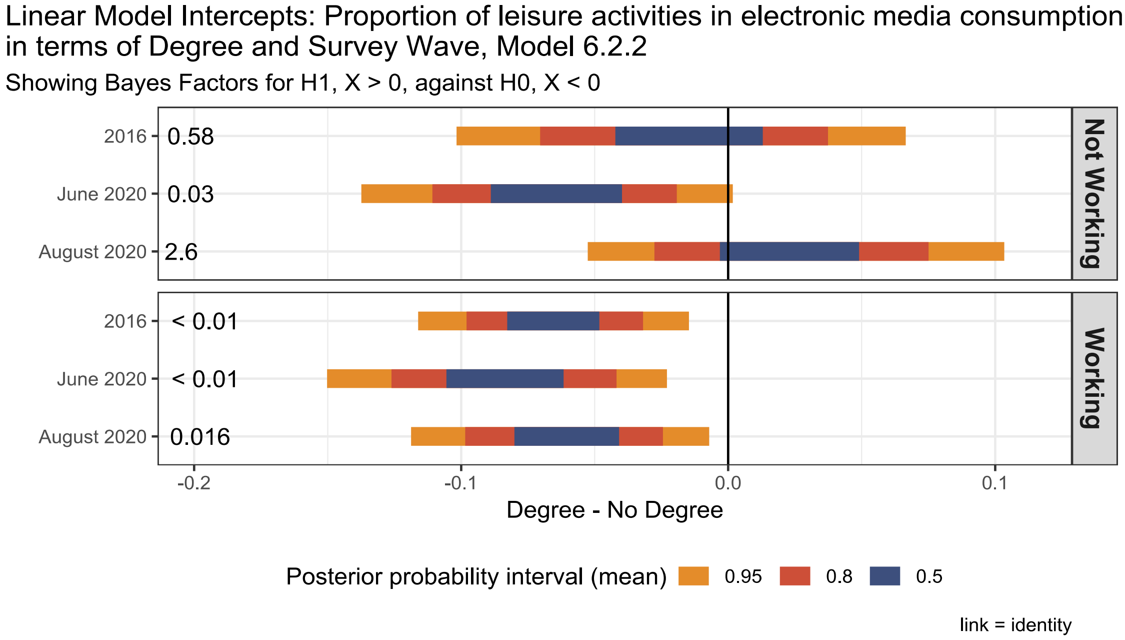

Figure 6.2.6

It is worth considering the relation between daily routine, as categorised by diary day cluster (as defined and explored in section 4) and the proportion of leisure time spent in electronic media consumption. Model 6.2.3 predicts the proportion of leisure activities in the consumption of media in terms of diary day cluster, including age, sex and class as control variables, once again using a Gaussian response distribution. The results are shown in Figure 6.2.7.

The first major pattern is that clusters 4, 5 and 6, the most regular 9 to 5 workdays (Figure 4.1.1), along with cluster 23, the equivalent pattern for unpaid work (Figure 4.2.1), have the strongest association to spending leisure in media consumption, with 95% credible intervals far from 0. There is moderate to strong evidence (if not with the 95% credible interval) that many of the other 9 to 5 workdays, cluster 3, 8, 10, along with the semi-regular unpaid workday cluster 22 share this association. Compared to other workdays, it seems that the regular rhythm of a 9 to 5 workday goes hand in hand with an evening in front of the TV.

The other principal pattern in Figure 6.2.7 is that many of the 'Disrupted Days' (cf. Figure 4.4.1), with widely shifted sleep patterns, have some of the least leisure time in passive media consumption. Rather than implying a state of depressed apathy between bed and TV (perhaps this is the case for cluster 26), clusters 19, 20 and especially 35 (along with the highly interrupted leisure of cluster 17) are extremely strongly associated with more varied use of leisure time. I suggested above (in section 4.4) that cluster 35 is a sort of hyperactivity, which is borne out by Figure 6.2.7: it seems to be an attempt to use the full day in a wide variety of activities. Overall, it seems that a disrupted sleep pattern is associated with low levels of consumption of electronic media. Meanwhile, media consumption is more typical of days with a late start such as cluster 28 and 32 (with strong evidence if not credible at 95%).

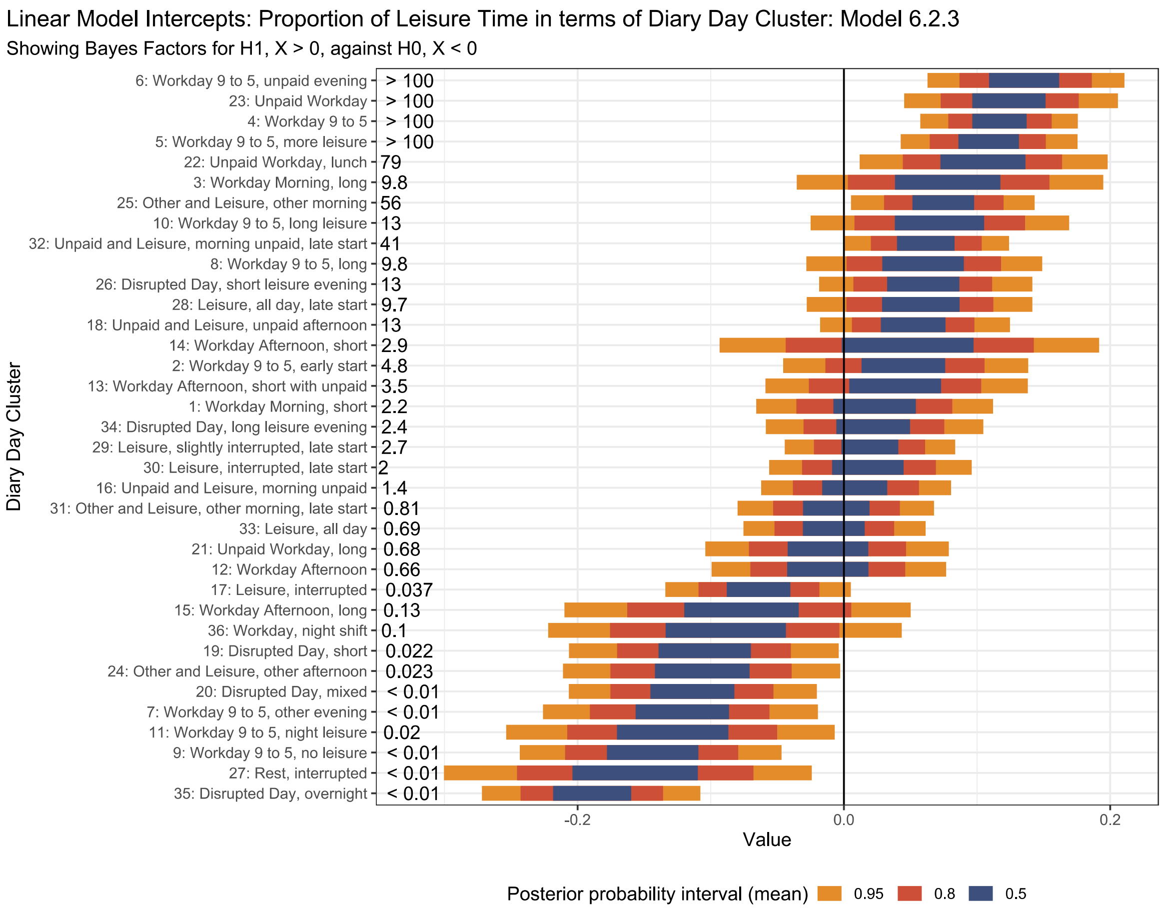

Figure 6.2.7

6.3 Forms of Engagement in Leisure Activities and Mental Health

Some theorists, particularly Han (2015) and Petersen (2020), consider that an over-intense commitment to and engagement in leisure activities, especially those that are linked to social competition and self improvement, can be harmful to mental health as part of ‘burnout’ (section 1.2). Voracity does not seem to be linked to the mental health indicator available, however there is a link between mental health and the proportion of leisure activities represented by the consumption of electronic media.

The mental health indicator used in this study has been described above (section 3.3). Briefly, it is a combination of eleven questions asking respondents in the 2020 waves to subjectively rate whether aspects of their feelings and behaviour had improved or declined since lockdown began. The subjective questionnaire is not ideal, but it is used as the best available. The indicator is continuous from 0 to 3, where 0 indicates improved mental health in lockdown, 1 indicating no change, 2 indicating worse, and 3 much worse.

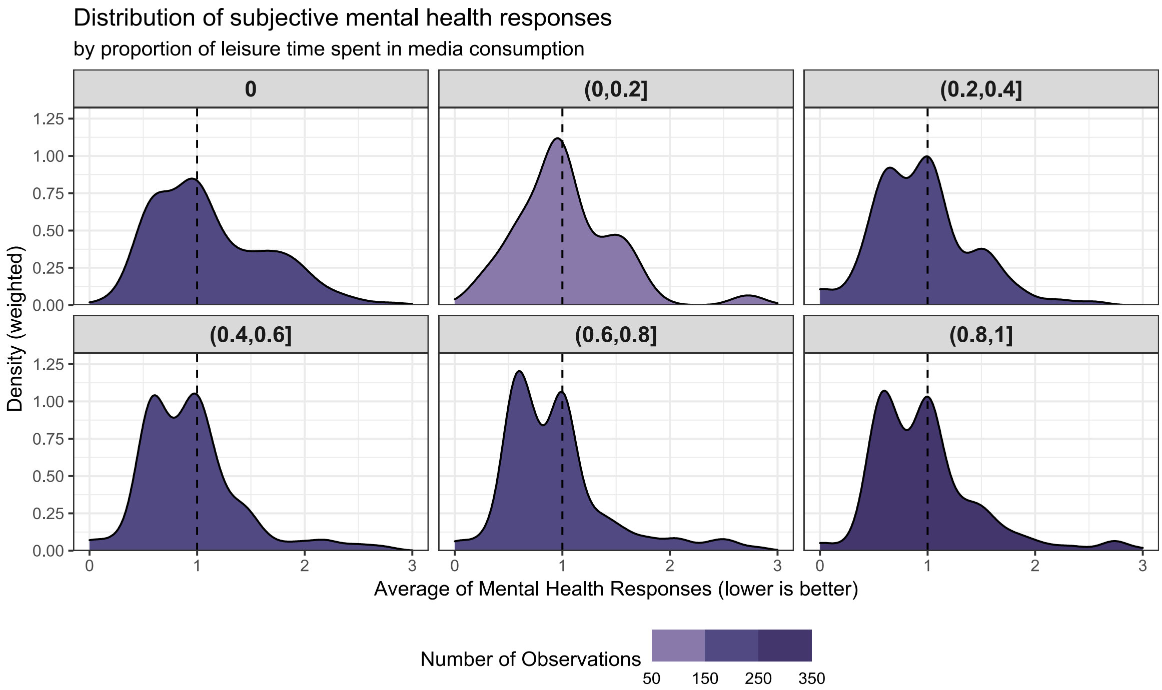

Figure 6.3.1

Figure 6.3.1 shows the distribution of these responses, divided by the proportion of leisure spent in media consumption. The vertical dashed line indicates the response ‘no change’; mass to the left of this line corresponds to better subjectively evaluated mental health since lockdown began, and mass to the right worse. The June 2020 and August 2020 waves are combined. It can be seen that the best mental health is to be found in respondents who spent between 60% to 80% of their leisure activities consuming media (the middle bottom panel) and the result is similar in those who spent more than 80%. As this proportion declines below 60%, mental health worsens, becoming worst of all in those who consumed no electronic media.

Model 6.3.1 predicts this indicator in terms of the proportion of leisure in media consumption, including age, sex (which is strongly related to the mental health indicator:

women report worse mental health in lockdown on the whole) and class as controls, as well as work status in lockdown. The modelling specification and sample is otherwise the same as the previous Model 4.6.1 (1 332 diary days, after excluding 1083 with no mental health questionnaire, mostly in 2016, and 55 for whom work status in lockdown is NA, along with 174 for whom the proportion of leisure is NA).

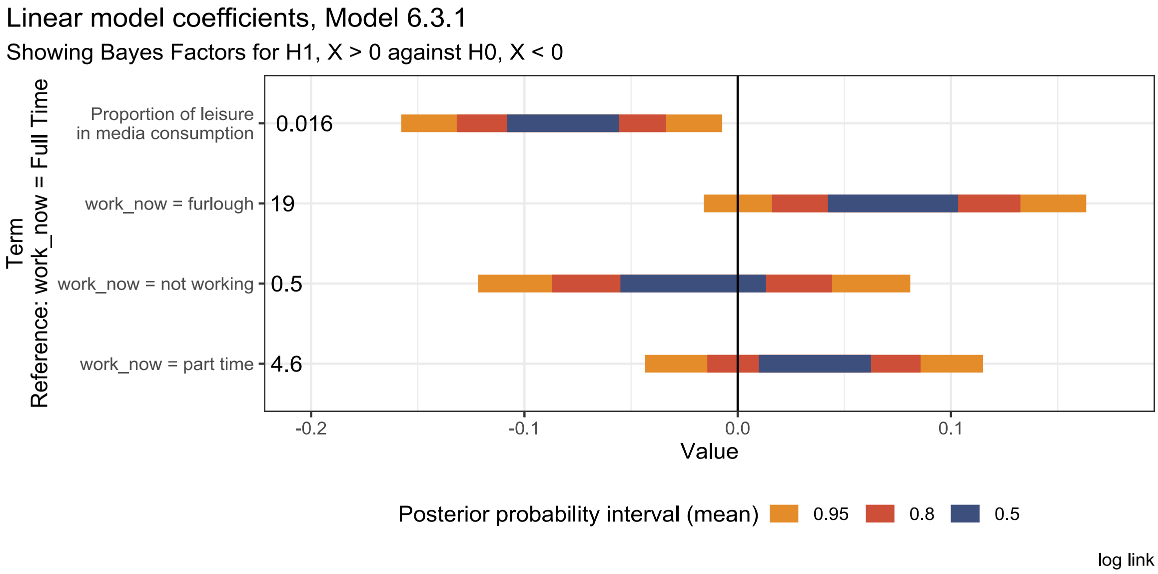

Figure 6.3.2

The results for the proportion of leisure time and work status in lockdown are shown in Figure 6.3.2 (full results in Appendix B). A higher value corresponds to a higher value of the mental health indicator, and so worse mental health. Starting with work status, compared to the reference category of ‘full time’, there is little evidence for a difference in those not working or those on part time, but strong evidence for a negative impact on mental health in furlough (if the credible interval slightly overlaps 0 at 95%). An effect with stronger evidence than furlough, however, is that of the proportion of leisure spent in media consumption; the credible interval here does not overlap 0 and the Bayes factor indicates very strong evidence for a positive impact on mental health, confirming the implication of Figure 6.3.1. The mean value implies that a the difference between a proportion of 0 and 1 is equivalent to almost a whole point (0.92) on the mental health scale. In short, more consumption of electronic media, as a proportion of time in leisure activities, is associated with better mental health in lockdown, even when employment status in lockdown is taken into account.

6.4 Engagement in Leisure Activities: Overview

Lockdown meant an increase in free time for many, and lessened the relevance of conventional norms governing time use for everyone. The effects of the resulting *anomie* might be thought to be most evident in patterns of leisure activities, time when the obligations of work, housework and childcare, still very much present in lockdown, do not apply and people by definition have the most control over how they spend their time. Moreover, given that leisure activities are cultural practices and so to great extent determined by educational level as part of the reproduction of social class, it might be expected that educational level is a key determinant of responses in lockdown.

Two aspects of engagement in leisure activities have been considered in this section. Voracity, the number of different leisure activities per day, is a measure of the intensity of leisure activity through their variety, which is linked to omnivorousness as a marker of social class and implies increasing cultural capital. Meanwhile, the proportion of leisure time spent in electronic media consumption is a rough measure of the internal quality of leisure time and the extent to which it is (not) spent in activities that are considered self-improving.

Both of these indicators show a clear relation to educational level, at the high level of agglomeration used here (necessitated by the small sample size): holders of university degrees vs. those without. In all survey waves, degree holders' leisure activities are more voracious and less characterised by the consumption of electronic media than those of non-degree holders. In the case of voracity, this follows the previous findings of Southerton (2006) and in particular Sullivan and Katz-Gerro (2007).

However, both indicators also show a single consistent pattern during lockdown. The 'gap' between degree holders and non-degree holders *narrowed.* Relative to degree holders, non-degree holders engaged in leisure activities more voraciously, with a higher proportion of time spent in activities other than the consumption of electronic media, in August 2020 compared to 2016. In the former case, the effect was cumulative over June 2020 until August, while for the latter the gap widened in June, and narrowed in August. The first result in particular is complimentary to the large scale French study of Jonchery and Lombardo (2020) who found that people diversified their leisure activities in lockdown, and that inter-class disparities in this regard decreased (p.7). Their study is also an excellent source for the detailed breakdown of leisure activity during lockdown, which could not be investigated here due to the limitations of sample size.

Moreover, this pattern remains even when differential rates of stopping work during lockdown are controlled for. In the case of voracity, it is degree holders who decreased the voracity of their leisure activities, with some indication that this tendency is a little stronger among those who stopped work in lockdown; in the case of consumption of electronic media, it is non-degree holders, both working and not working, who decreased the proportion of leisure time spent in this activity.

It might have been expected that the *anomie* of lockdown would, firstly, decrease time pressure on the ‘harried leisure class’ and remove pressures to accumulate cultural capital as part of social competition (e.g Bourdieu 1992, Gershuny 2005, Petersen 2020). On the other hand, the contradictory perspective of Beck (1992) and Binkley (2009) would suggest that uncertainty over future work prospects would redouble ‘useful’ leisure time practices and attempts to ‘productively’ use leisure time in this regard (cf. sections 1.2 and 1.3). Meanwhile, both of these approaches reflect predominantly higher-educated approaches to spending leisure time, and it must be kept in mind that non-degree holders have approaches to leisure time outside of these two somewhat *misérabiliste* perspectives.

The results of this section suggest that in the case of voracity, a decrease in time pressure on higher educated members of society who are working – the ‘harried leisure class’ – did indeed decrease their voracity in leisure activities. This tendency persisted even during the return to work in August 2020. On the other hand, when the consumption of electronic media is considered, there is no evidence for change in behaviour among the more educated: it is those without university degrees, out of work, who increased and then strongly decreased their consumption. It could be hypothesised that this reflects changes in family time, given that the television remains a focus for family activity in working-class families (Masclet 2018); this is somewhat supported by section 8.1 which shows a similar the pattern across survey waves in time spent with other family members, for respondents in less qualified occupations. An alternative explanation for the large decrease in August 2020 is that those without university degrees, still out of work even as lockdown appeared to be ending, responded to the situation by expanding the amount of time they spent in leisure activities, such as a hobby, they already engaged in previously (as opposed to a larger variety, which would be measured by voracity). This may have been an attempt to find alternative forms of self-improvement and self-realisation, as suggested by the perspective of Beck and Binkley. However, the data available here is too general to allow more than speculation without more detailed qualitative studies.

The proportion of leisure time spent in electronic media consumption appears to be positively associated with regular 9 to 5 workdays, and negatively with highly disrupted and irregular daily routines. Meanwhile, the result of section 6.3, linking a low proportion of leisure in electronic media consumption to worse (subjectively assessed) mental health in lockdown, even once lockdown employment status (e.g furlough) is controlled for, appears to be strong evidence for Han (2015) and Petersen (2020)'s theorisation of 'burnout'. Spending a higher proportion of time in the consumption of electronic media, an activity which, at a high level of aggregation, is on the whole perhaps the least self-improving and least related to the aggregation of cultural capital, is associated with better mental health in lockdown.

7. Sleep Patterns

Previous studies using time-use surveys to measure sleep patterns have concentrated either on the (inverse) relationship between work time and sleep time (Biddle et al. 1990, Basner et al. 2007, Chatzitheochari and Arber 2009), or on male-female inequalities in sleep time or quality (Hislop and Arber 2003, Burgard and Ailshire 2013), in the latter case using qualitative as well as quantitative data (e.g Maume 2010). This study, however, takes a different approach. The perspective whereby work is a key determinant of sleep is retained, but the relation examined is not that between the *quantity* of work time and sleep time, but between workdays and the *timing* of sleep patterns, as well as changes to the total quantity of sleep during lockdown.

The perspective adopted here is that waking up late, and going to sleep late, is a key characteristic of non-workdays. When days do not contain the obligations of work, not only the quantity but the timing of sleep changes, most notably as regards the possibility of a lie-in. I suggest that this aspect of non-workday time use is part of pre-lockdown weekly routine, and part of the conceptual distinction separating workdays from non-workdays, days 'on' and days 'off': a way in which a day is signalled as 'your own', or a 'day of rest'. However, it will be shown in the analysis that in lockdown, this behavioural distinction between workday and non-workday routine disappeared, and did not reappear even as restrictions lifted in August 2020. The total quantity of sleep time is also considered, to see if people changed their overall amount of sleep in lockdown, as whether lockdown had a stabilising or disruptive effect on overall sleep pattern, when waking and sleeping times are considered in combination.

7.1 Wakeup Time

Wakeup time is simply measured as the time of the first time period that is not coded as 'Sleeping' on either primary or secondary activity vector. Using the combination of the two vectors considers an entry of, say, 'Sleeping' on the primary vector but 'Watching TV, Video' on the secondary vector, (which might imply an activity taking place in bed) as having woken up. The indicator is therefore a measure of 'waking up' rather than 'getting up'. In order to estimate the impact of different forms of work over survey waves, such as the effects of the shift to homeworking and of stopping work during lockdown, ‘Day Type’ (coding is described in section 3.3) is used as an interaction variable in the analysis. The analysis also includes qualification, as a simple two-level variable of ‘Degree’ and ‘No Degree’, since it appears that, in the case of wakeup time, degree holders responded to lockdown quite differently to non-degree holders.

Figure 7.1.1 shows the cumulative percentage of respondents who had woken up by a given time, in terms of Day Type, Degree and Survey Wave. A vertical dashed line is given at 9am for reference. On non-workdays, it can be seen that respondents without a degree get up earlier in the 2020 waves compared to 2016. especially in August. This is also true of degree holders who continue to work during lockdown; those not working during lockdown, however, wakeup much later in June 2020 only. Turning to workdays, those without a degree show little pattern when working outside the home, and while there appears to be a big shift to late wakeup times when working at home in June 2020 only, this result is less important than it appears because there are very few people without degrees working from home in the 2016 survey wave. Degree holders, meanwhile, get up later in June 2020 compared to 2016 on outside workdays, and even later in August 2020; the pattern is most pronounced in late risers (to the right of the graph). For home workdays, there is a slight shift to working earlier from June to August 2020.

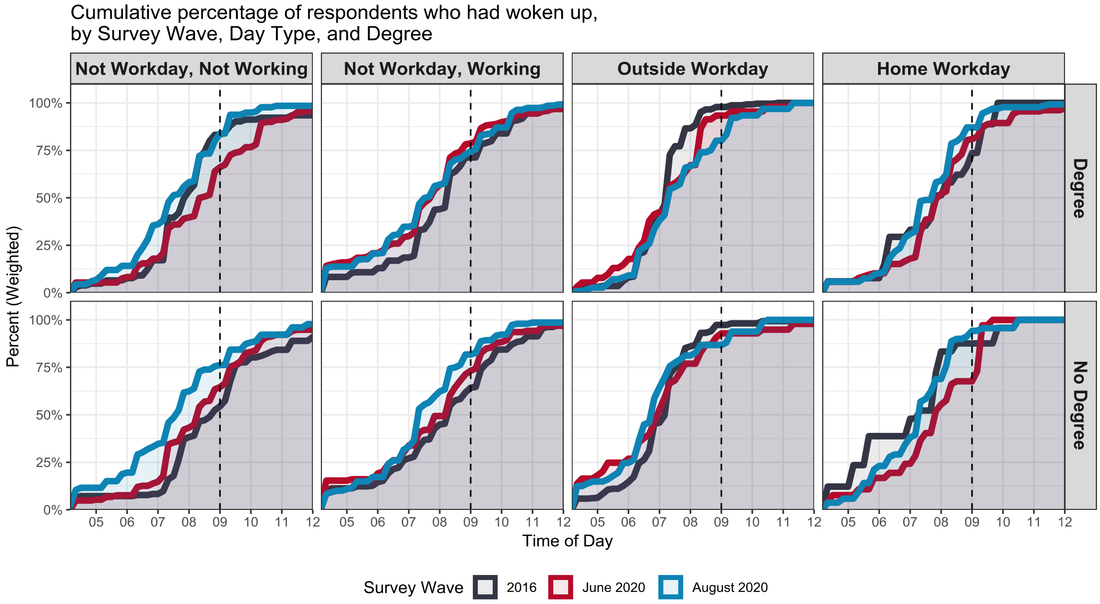

Figure 7.1.1

Model 7.1.1 predicts wakeup time in terms of the interaction of Degree, Survey Wave and Day Type while controlling for Age and Sex. As in all models in this section where Day Type is a predictor, 12 cases where Day Type is *NA* are excluded. A Student response distribution was used, justified both by goodness of fit and conceptually, since early and late risers are much more common than would be implied by a Gaussian process. The results are shown in Figure 7.1.2 (full results in Appendix C); a positive value corresponds to a later wakeup time.

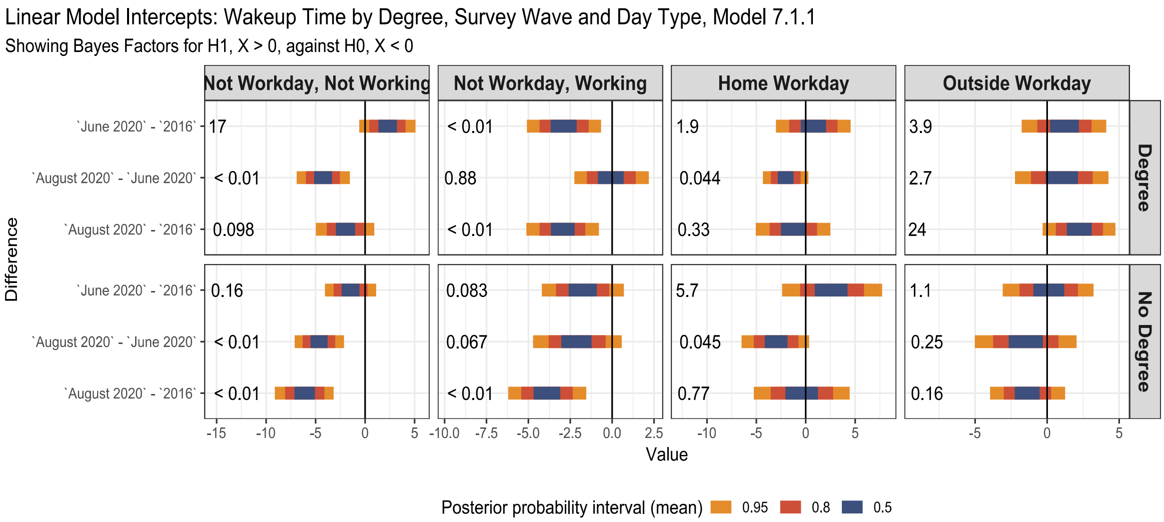

Figure 7.1.2

On non-workdays, for those not working, wakeup times in June 2020 compared to 2016 vary according to qualification: there is moderate evidence for both later wakeup times for degree holders and earlier among not degree holders (cf. Figure 7.1.4 below). In August 2020, however, both groups wake up earlier compared to June 2020. The pattern is different on workdays when the respondent is working, however: there is strong evidence both groups shift to earlier wakeup times, degree holders in June 2020, non-degree holders gradually in June and then continuing into August.

Turning to workdays, we can compare Figure 7.1.2 to Figure 4.1.8 above, where working from home temporarily leads to many afternoon work schedules, but these switch back to regular '9 to 5' days in August 2020. Here it appears that while there is no conclusive evidence that the shift to afternoon work schedules led to a change in wakeup time when working from home in June 2020 compared to 2016, when regular '9 to 5' days had resumed by August, both degree and non-degree holders woke up earlier when working from than they had in June 2020. The main pattern on workdays outside the home is that degree holders wakeup later in August 2020 than they had in 2016. with no change for non-degree holders.

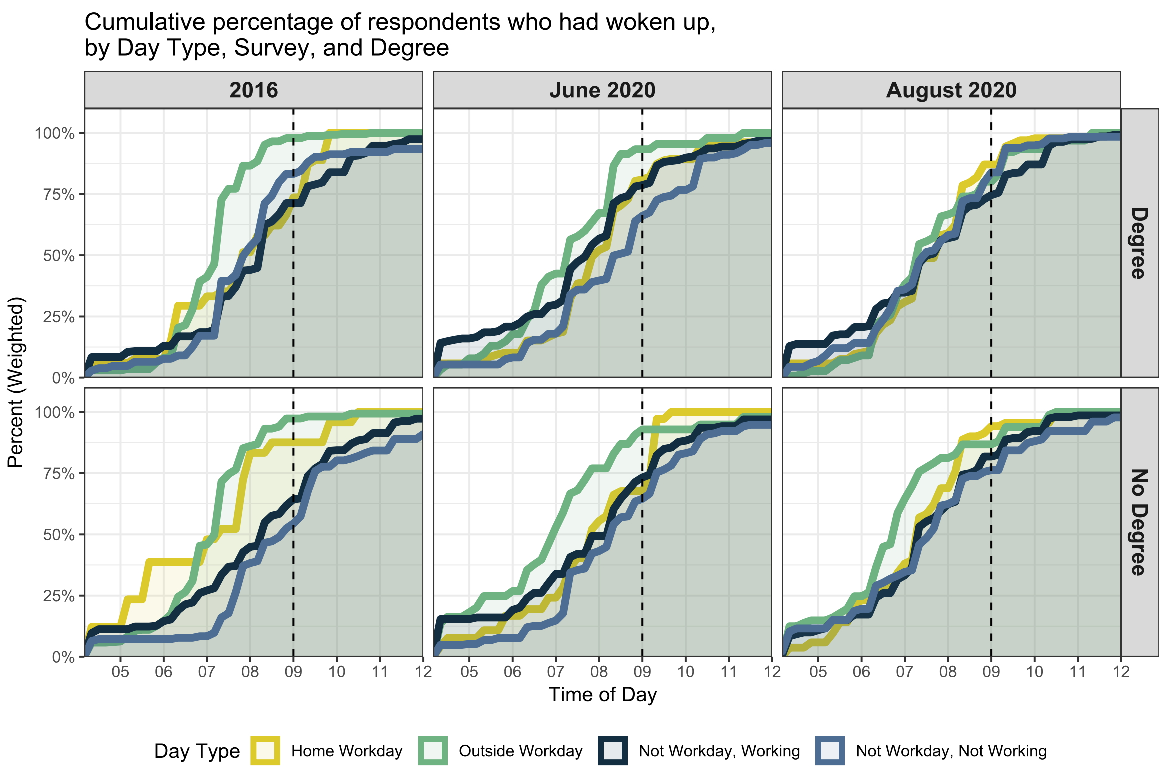

Figure 7.1.3

Figure 7.1.2 establishes that there is strong evidence for many shifts in wakeup times between survey waves. However, finding a coherent explanation for the many disparate patterns requires a different perspective: the difference between workday types. Figure 7.1.3 shows the same cumulative proportions of respondents who had woken up as Figure 7.1.1, but arranged so that Day Type is contrasted rather than Survey Wave. This allows considering the extent to which the different types of day resemble each other. For both groups, from 2016 to August 2020 it can be seen that the trend of getting up later on outside workdays contributes to a convergence in wakeup times for all four kinds of day. Workdays and non-workdays begin to resemble each other as an early workday morning becomes less common, even among those resuming work outside the home in August 2020 (with the exception, in this last case, of non-degree holders). Meanwhile, the shift in June 2020 to later non-workdays when in work, and earlier workdays when working from home, means that wakeup times on these two types of day, which were quite distinct in 2016, become almost identical in June 2020. Meanwhile, again for both degree holders and non-degree holders, the shift to earlier wakeup times when not working brings these days into line with all three kinds of day when working, to a more marked extent in the case of those without a degree for whom the difference was most stark in 2016. The strength of evidence for these effects has been confirmed in Figure 7.1.2.

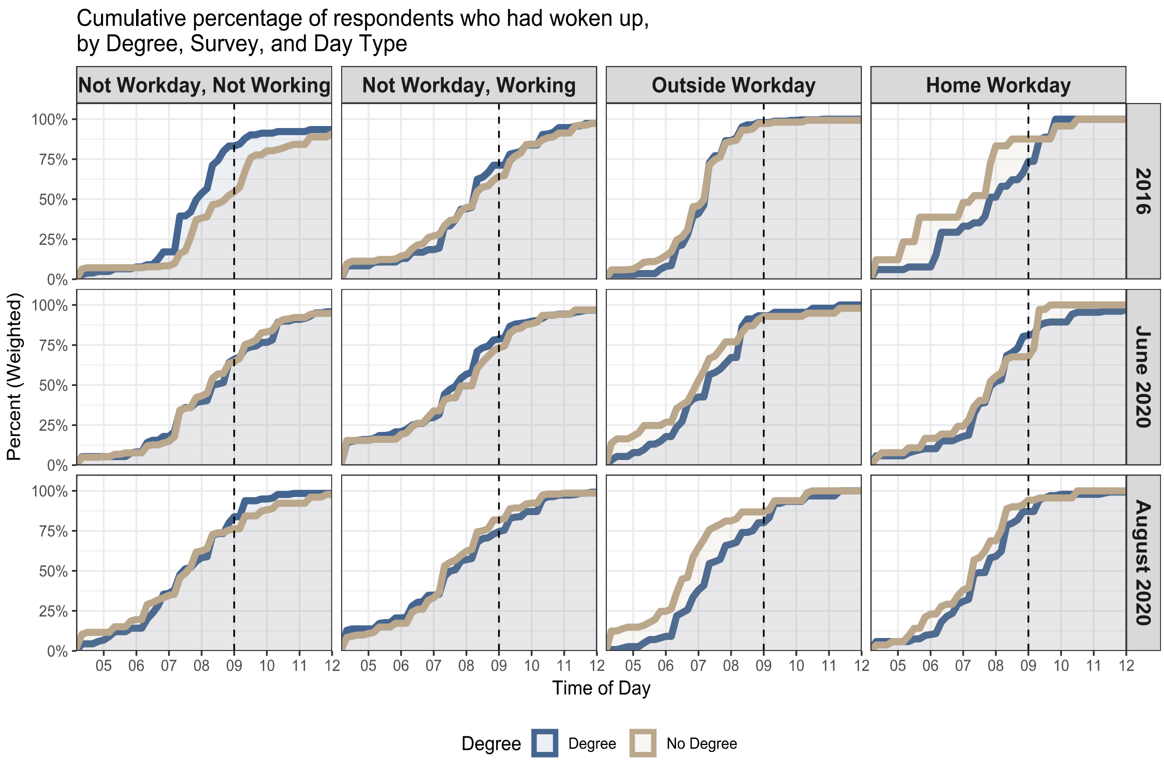

Figure 7.1.4

What does this mean for inequalities between those with a university degree and those without? Figure 7.1.4 plots the same cumulative percentages once more, now contrasting those two categories. On non-workdays, there is one clear difference between degree holders and those without: the former wake up earlier on non-workdays when not working, in the 2016 survey wave. This pattern vanishes in June 2020, and is not re-established in August (even though both categories are waking up earlier than in 2016 Figure 7.1.1). This is supported by Model 7.1.1: the Bayes factor for the hypothesis that degree holders wake up earlier than non degree holders is very strong for 2016, at > 100, while the Bayes factor that the August 2020 value for Degree – Not Degree is larger than the 2016 value is 39.5 (not shown; calculations can be found in the code appendix).

Meanwhile when working outside the home, Figure 7.1.4 shows that in 2016 those without degrees are more likely to wake up before 7am (since they are less likely to work 9 to 5 jobs: section 4.1). The gap widens through lockdown into August 2020 as degree holders wake up later on workdays outside the home. Turning again to Model 7.1.1, the Bayes factor for the hypothesis that degree holders wake up later on outside workdays on 2016 is merely anecdotal at 1.4, but extremely strong, > 100 for August 2020, while the Bayes factor that the difference in August 2020 is larger than in 2016 is very strong at 37.7 (not shown). As for home workdays, those without a degree wake up earlier in 2016 and again (less so) in August 2020. The evidence in this case however is weak, given the small number of respondents without a degree working from home: the Bayes factor for the hypothesis that degree holders wake up later on home workdays is 4.7.in 2016 and 6 in August 2020, and an anecdotal Bayes factor of 2 for the hypothesis that the June Value is smaller than these (calculations can again be found in the code Appendix C).

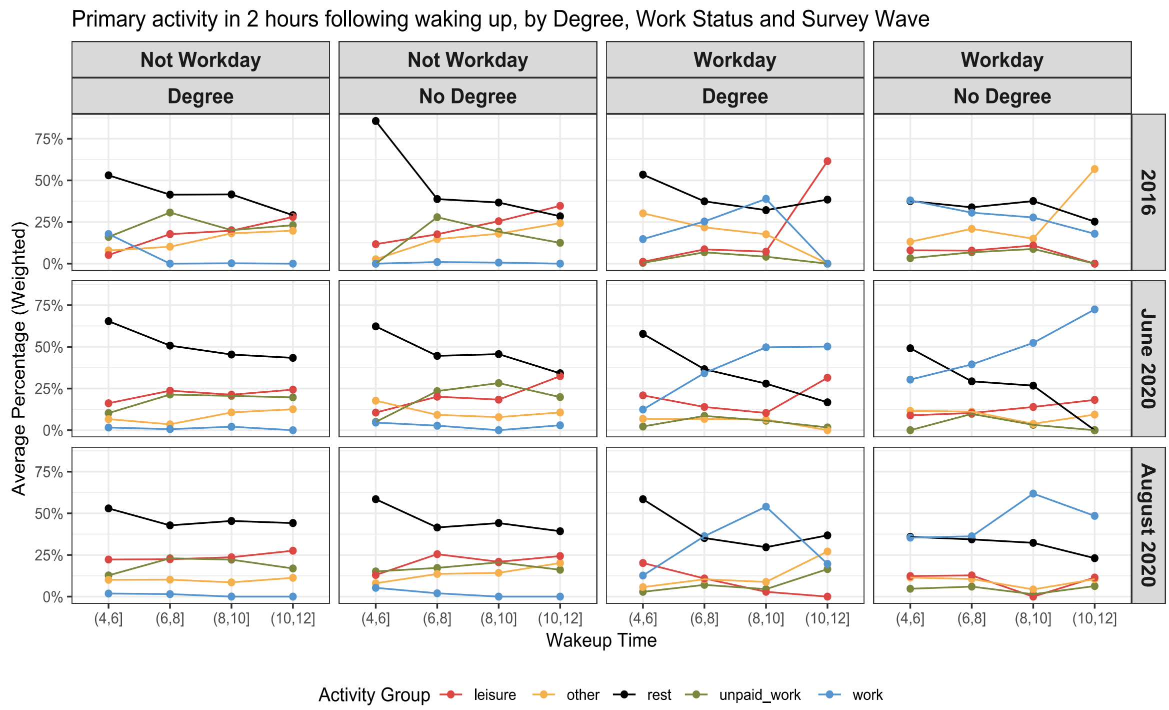

Figure 7.1.5

Why did people wake up earlier (or later) in lockdown compared to 2016? This is not of course a question that can be fully answered with the merely quantitative data available. By supposing, however, that what people do after waking is in many cases why they woke up, some inferences can be made by quantifying the primary activity in the two hours after waking up, as in Figure 7.1.5. The grouping of activities is the same as that used in the typology of daily routines (section 3.1 and section 4). Wakeup time has been subdivided into 2 hour slots, and the average percentage of time spent by respondents in the two hours following waking up is shown, sorted by Degree and whether the day was a workday.

While it was not possible to to verify the size of the effects by modelling, some trends are still apparent. The earlier people wake up, the more time they spend in 'rest' or self-care activities in the following two hours. Moreover, on non-workdays the principal other categories of activity are 'unpaid work' (such as housework) and leisure; there is no solid indication that any one of these is more important than the other, with perhaps a slight indication that leisure increases compared to unpaid work for people waking earlier than 8am in the 2020 survey waves compared to 2016. Meanwhile on workdays, a later wakeup time means going 'straight to work'; only those waking up before 6am spend little of their first two waking hours working – and non-degree holders are much more likely to go to work early. Meanwhile among both degree and non-degree holders, especially the former, leisure is more common than unpaid work among early risers on workdays in the 2020 survey waves.

The overall pattern of shifts in wakeup time during lockdown is multifaceted, but there are some clear trends. In 2016, there were great differences in wakeup time between workdays outside the home (early) and non-workdays (late); home workdays were intermediate, waking up early in the case of those less qualified and late in those more qualified (which perhaps reflects differential degrees of control over home work hours). Over lockdown, however, people woke up earlier on non-workdays and later on workdays, leading to a convergence in wakeup times across all day types. The exception is non-degree holders working outside the home, who continue to wakeup early; it would seem, from analysis of activity in the two hours after waking, that this is because of work obligations.

It should be kept in mind that the shift on ‘Not workday, not working’ in June 2020 compared to 2016 is greatly affected by those who stopped work during lockdown, who swelled the size of this group, especially among non-degree holders (Figure 6.1.6). This may be the cause of the shift in wakeup times on these days. It is nonetheless striking that the shift is to *earlier* rather than later wakeup times, and that by August 2020 wakeup times for all kinds of day are very similar, suggesting that in this regard people tended to bring the ‘work habit’ of early waking to non-workdays, rather than the other way around.

A second pattern is observable on non-workdays, in the case of those not working. In 2016 degree holders woke up much earlier than non-degree holders on these days. Over lockdown, however, both groups woke up earlier, non-degree holders more so, so that the gap between the two groups vanished. There is a direct parallel here to the result in section 4, where early starting daily routines dominated by leisure activities are typical of less qualified occupations (Figure 4.3.3). Waking up early without the institutional obligation of work to do so, might be seen as a ‘productive’ use of free time (cf. section 1.3), not ‘wasting’ the day in bed. On the other, it may be because of obligations of housework and childcare, or in order to spend time with other family members who wakeup at that time, such as a partner on an early shift (cf. Section 7, where this question is investigated further). Analysis of early morning activity suggests that both leisure and unpaid work activities are equal in time, which does not allow distinguishing or ruling out either of these two potential causes. It was not possible, moreover, to find evidence for a direct link between early wakeup time and time spent with other household members. As a final point, the overall result, that non-workdays start earlier in lockdown and after compared to 2016 should be seen along with the result of Figure 4.7.2, that non-workdays with an early start are linked to worse mental health.

7.2 Sleeping Time

The time of going to sleep, 'sleeping time', is measured by the time of the first period that is labelled 'Sleeping' on both the primary or secondary activity vector (or only one if the other is not available because of non-response), counting backwards from the end of the diary day (at 4am). It is therefore a direct equivalent to wakeup time in the previous section, counting time labelled as 'Sleeping' on one vector, but also performing another activity, as not yet asleep. Day Type is once again included as a variable, while in this case there did not appear to be significant differences between qualification levels.

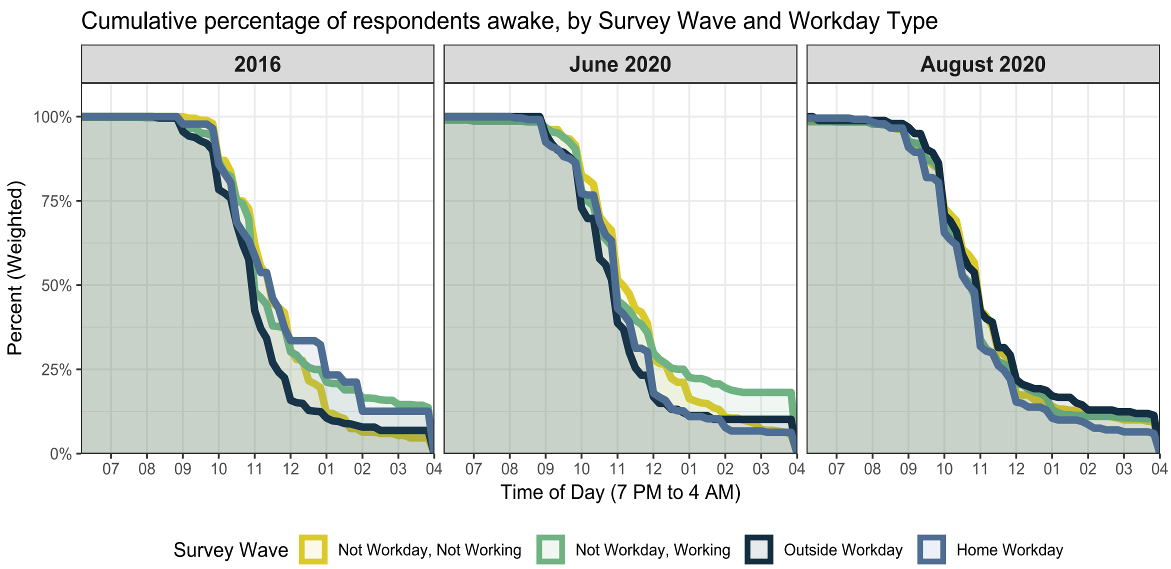

Figure 7.2.1

Figure 7.2.1 shows the percentage of respondents awake, by day type and survey wave. The graphs end at 4am, since that is the end of the diary day. As in the case of wakeup time (Figure 7.1.3), the differences between types of day, very distinct in 2016, disappear by August 2020. In 2016 people go to bed latest on home workdays and on non-workdays (especially those working), and earliest on days working outside the home. In June 2020, this has shifted so that home workdays resemble those outside the home rather than non-workdays, and in August 2020 all day types resemble each other.

The cause of these changes is visible in the alternative presentation of the same percentage figures in Figure 7.2.2. On non-workdays, there is a slight shift to earlier sleeping times over survey waves, especially in the case of those working. Meanwhile there is an increase in those staying up overnight on workdays outside the home, and a marked shift to earlier sleeping times on home workdays. The reason for growing similarity between day types is a shift on non-workdays, and especially days working from home, towards a daily schedules situated earlier in the day, bringing them into line with workdays outside the home. The shift is not entirely in one direction, however, there is also an increase in late nights on workdays.

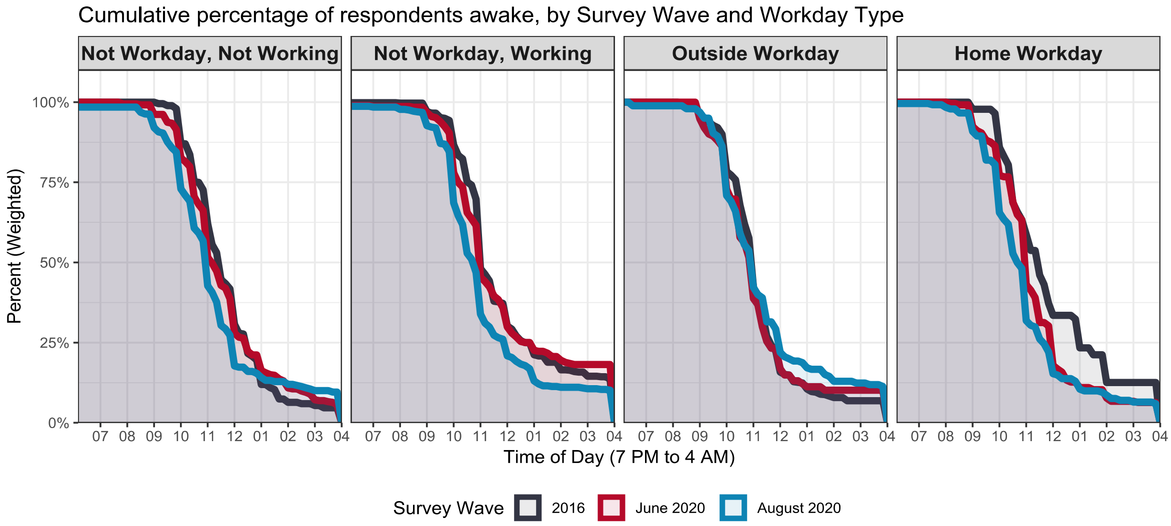

Figure 7.2.2

Model 7.2.1 predicts sleeping time in terms of the interaction between day type and survey wave, controlling for age, class and sex. A student response distribution was used, for the same reasons as in the case of wakeup time (Model 7.1.1). In this case, however, the standard deviation (sigma) was estimated as well as the mean (mu), since there are patterns not only in the change in the average time, but also in the spread of times, which reflects the proportion of people staying up very late or overnight (or, theoretically, going to sleep very early, but there are very few instances of this, which is a slight deficiency of the model fit). The main results are shown in Figures 7.2.3 (full results are in Appendix B).

Figure 7.2.3 shows the differences between survey waves, reflecting Figure 7.2.1 above. A positive value of mu indicates a shift towards a later sleeping time, and of sigma towards a greater proportion staying up very late. There is extremely strong evidence, with 95% credible intervals outside 0, for a shift towards earlier average sleeping time in August 2020 compared to June 2020 and 2016 for all day types save 'outside workday'. There is also strong evidence (Bayes factor 0.027) for a shift in this regard in June 2020 compared to 2016, in the case of not workdays for those still in work. When considering the standard deviation ('sigma'), there is extremely strong evidence for increase in those staying up very late on outside workdays in August 2020 compared to 2016.

The results of model 7.2.1 accordingly confirm the pattern described. Average sleeping times shift earlier on all forms of day, except workdays outside the home, while more people stay up well past midnight on outside workdays. The overall effect of these shifts is to bring all day types into line with each other. It seems as though the effect of lockdown and the more or less temporary halt to work for a large percentage of the population has led to people behaving on non-workdays and home workdays as they previously did on outside workdays, importing the 'work habit' of an earlier bedtime to their non-workday behaviour, while is also a reverse effect in this case, a non-workday behaviour becoming more common on workdays: pulling a late night.

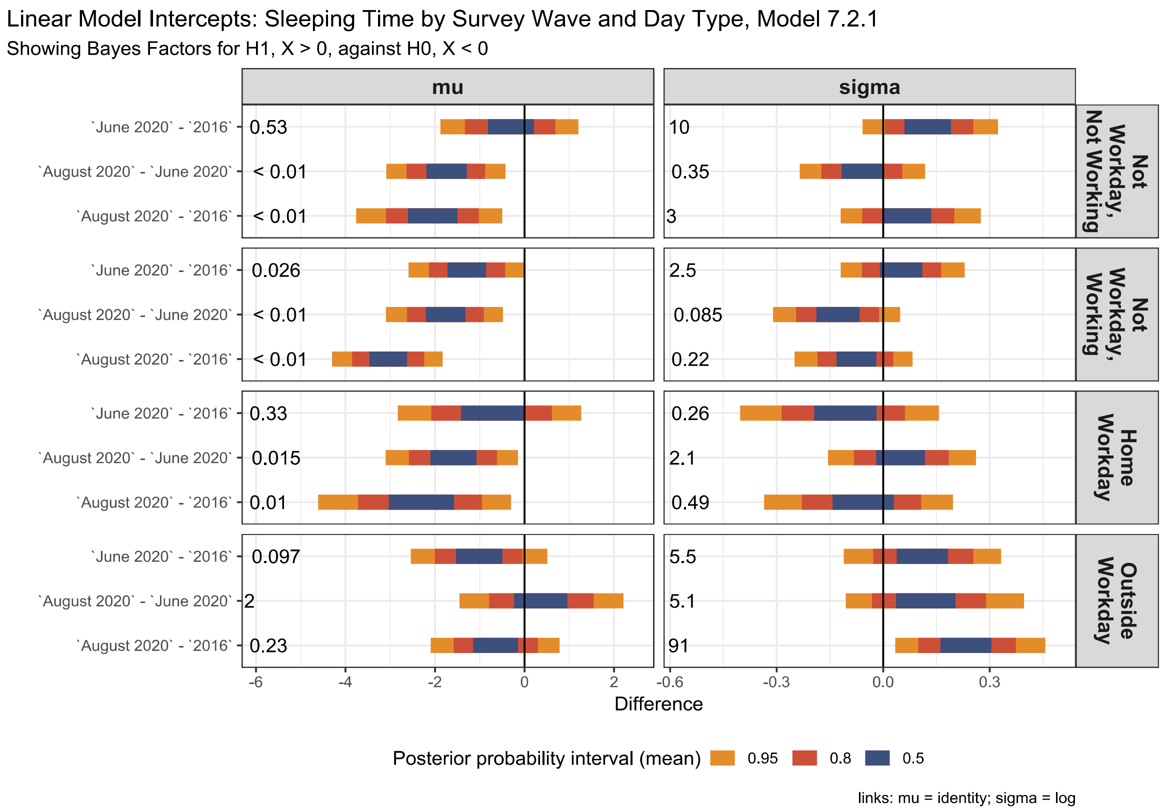

Figure 7.2.3

7.3 Total Amount of Sleep

Considering the times of waking up and sleeping does not, however, provide information as to the total amount of time spent awake and asleep. Did those who wake up early also go to sleep early, or not? Did lockdown lead to an increase or decrease in the total amount of sleep? Considering the total amount of sleep time in a diary day (thereby combining the quantity of sleep morning from 4am on with the evening and night until 4am the next day) is needed to answer this question. For the same reason as in the preceding sections, ‘sleep’ is defined as any period in which only sleep was coded in either activity vector.

Figure 7.3.1 shows the number of hours in a diary day spent sleeping. Considering all diary days, the left-most column in the left panel, the amount of time spent sleeping increased by almost half an hour on average in June 2020 compared to 2016. The division by workday shows that this increase is not only due to an increase in non-workdays; it is also due to an increase sleep time on workdays, particularly home workdays, as well as on not workdays for those working.

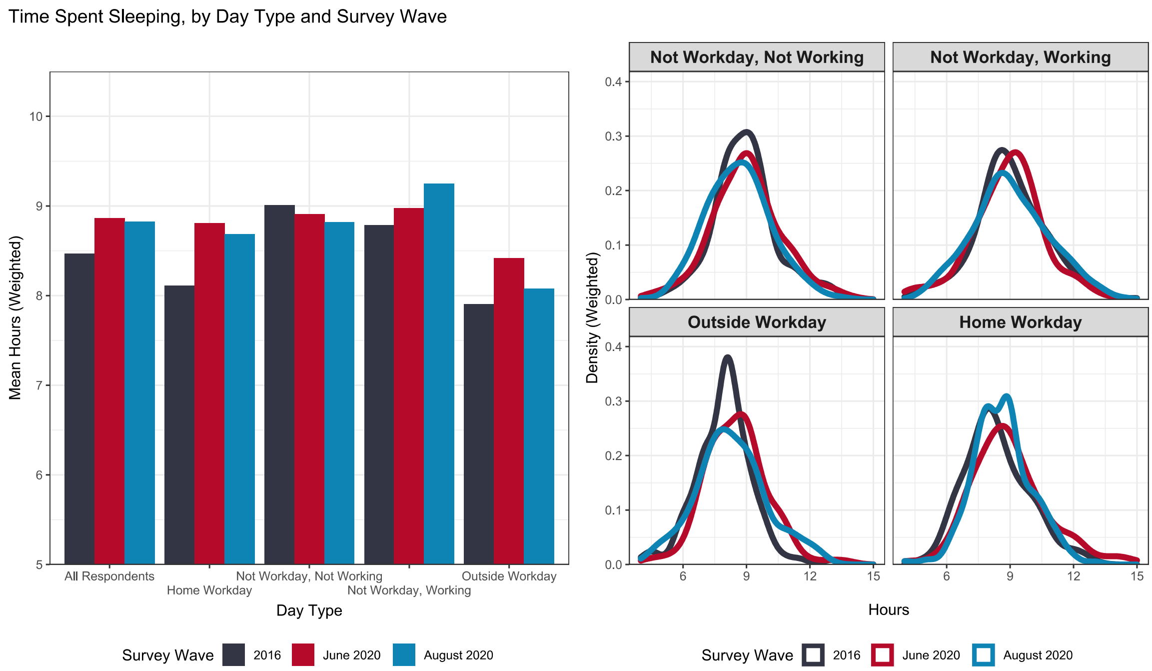

Figure 7.3.1

The average values are not the full picture, however. Patterns can be seen in the spread of time spent sleeping. The right-hand panel of Figure 7.3.1 shows that the spread of the distribution on all day types increased in June 2020 compared to 2016 and again for all work types except home workdays in August 2020. The change is particularly strong on outside workdays. This indicates an increase in days with very little or very large amounts of sleep; it corresponds to the 'disrupted' daily routines considered in section 4.4, where sleep patterns become widely shifted from the norm. It would seem therefore that waking and sleeping times did not necessarily move earlier in-sync, but that an increasing proportion of people slept for very long or very short periods.

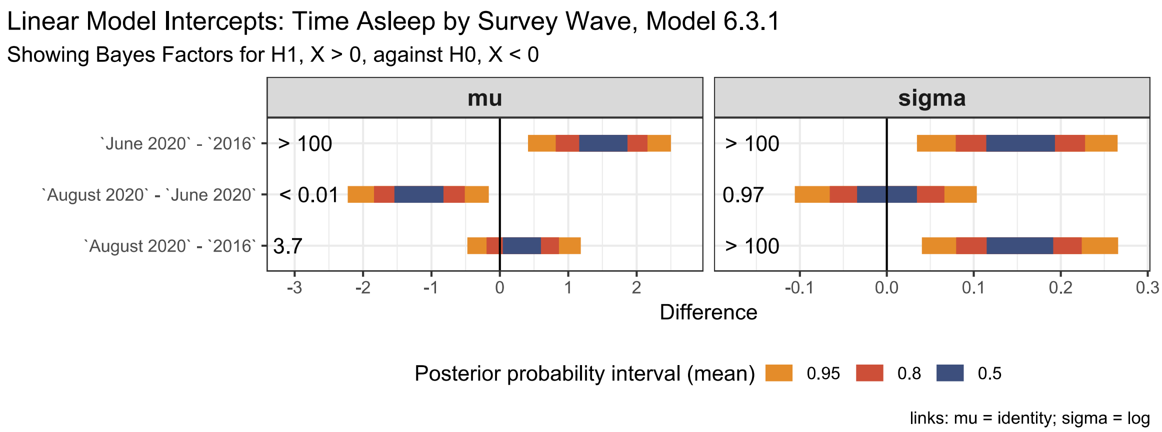

Figure 7.3.2

Model 7.3.1 fits a Student distribution (for the same reasons as Model 7.1.1 and 7.2.1 above) to predict sleep time in terms of survey wave, controlling for class, sex and age, and estimating the standard deviation ‘sigma’, as well as the distribution mean, ‘mu’. The main results are shown in Figure 7.3.2 (full results in Appendix B). The results for ‘mu’ show that Figure 7.3.1 is actually a little misleading as to the amount of sleep time in August 2020; once controls are included it appears to have decreased, and is in line with the amount of sleep in 2016. There is extremely strong evidence, with 95% credible intervals outside 0, for an increase in sleep time in June 2020 and decrease in August 2020, showing that people responded to the decrease in work and general relaxation of time use obligations in lockdown by increasing the amount of time spent asleep. There is also very strong evidence for an overall increase in spread in June 2020 compared to 2016; this however was maintained into August 2020. As people returned to work, the proportion of very disrupted sleep patterns did not decrease back to pre-lockdown levels.

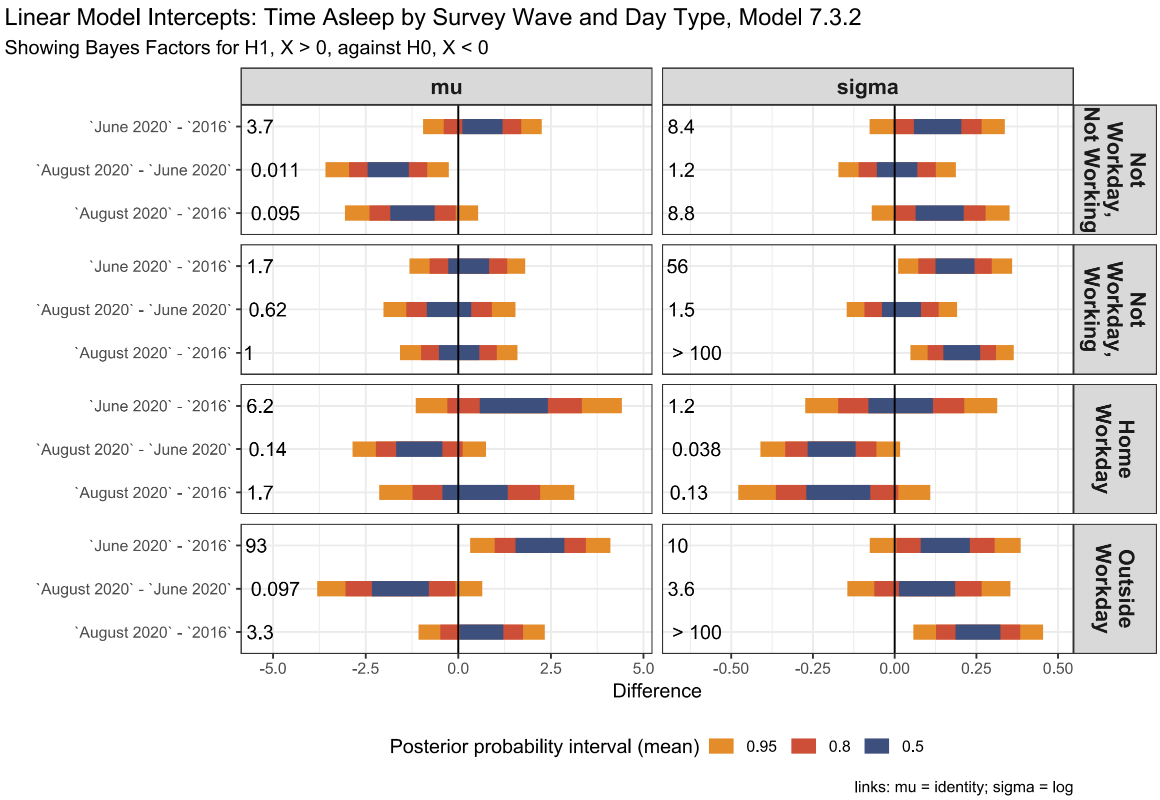

Figure 7.3.3

Model 7.3.2 adds the interaction predictor of Day Type to Model 7.3.1, keeping everything else the same. The results are shown in Figure 7.3.3 (full results once again are in Appendix B). This shows that the increase in average sleeping time in June 2020 compared to 2016 and decrease in August 2020, is strongest on workdays. Meanwhile, while it was not obvious from Figure 7.3.1, once the model's controls are included, there is in fact very strong evidence for a decrease in sleep time on not workdays for those who are *not* working, in August 2020 compared to June 2020 (0 falls outside the 95% credible interval). Meanwhile, the spread of sleep time increases most on not workdays for those working, and outside workdays, while decreasing for home workdays. This is in line with previous results in this study (sections 4.1, 7.2), where daily routines on home workdays become more regular, in line with 9 to 5 workday patterns, and outside workdays more irregular, in August and June 2020 compared to 2020.

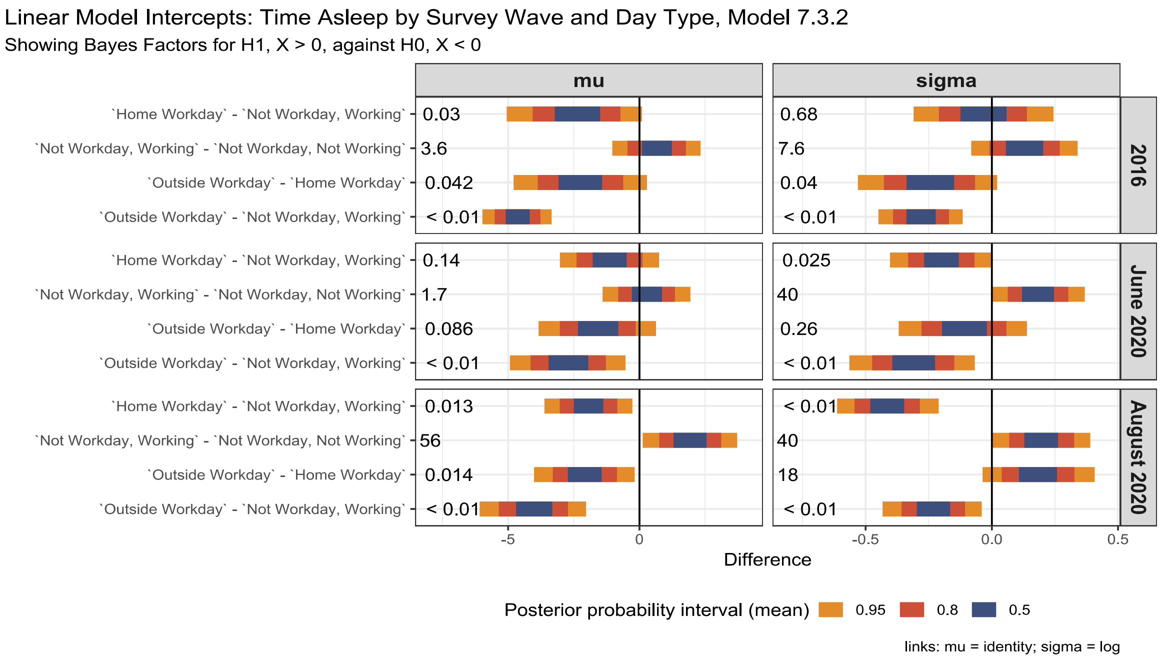

Figure 7.3.4

Figure 7.3.4 shows the results of Model 7.3.2 in terms of the difference between day types. It can be seen that there is strong evidence for less sleep on outside workdays compared to home workdays in all survey waves, which might indicate that the time 'gained' by not having to commute was converted into sleep time rather than other forms of activity. Meanwhile, comparing non-workdays between those working and those not, a gap opens up over survey waves so that while there is little difference in 2016 by August 2020 there is strong evidence that those working spend both longer sleeping and are more likely to have a widely divergent sleep time than those not working. The evidence for the difference between survey waves is only weak, however, with a Bayes factor of 5.7 for 'mu' and 2.2 for 'sigma' (not shown). Finally, there is on the whole strong evidence that workdays have less sleep and less spread than all non-workdays, in all survey waves. The increase in sleep time and in spread of sleep times in June 2020 compared to 2016 (Figure 7.3.2) can therefore be largely ascribed to the decrease in workdays.

7.4 Sleep Patterns: Overview

While continuing past research on the relationship between work and sleep, this section took the approach of looking principally at the *timing* of waking and sleeping, rather than the quantity that is typical of previous research (Biddle et al. 1990, Basner et al. 2007, Chatzitheochari and Arber 2009). As regards the times of waking up and sleeping, a pattern is observed in 2016 where workdays and non-workdays are very different: on workdays people wake up and go to sleep earlier than on non-workdays, which are characterised by (relative) lie-ins and late nights. In June 2020, however, the distinction lessens, as all forms of day start and end at more similar times. The trend continues into August 2020, where different kinds of day become indistinguishable. People get up earlier on non-workdays, both when in work and when not; waking times when working from home shift later, on outside workdays, earlier; sleeping times when working from home and on non-workdays shift earlier, while people more often go to sleep very late on outside workdays, bringing these days into line with other kinds of day. There is a global convergence of waking and sleeping times, where aspects of behaviour from both workdays and non-workdays become incorporated into a new generalised sleep pattern, that on balance has more in common with pre-lockdown workdays than non-workdays.

I wish to suggest that this behavioural shift will have eroded the conceptual distinction between workdays and non-workdays. Lockdown will for many have removed or changed the need to get up – and to go to sleep early in preparation for early waking the next morning. This is one of the destabilising effects on daily schedule that I argue create a degree of *anomie* of time use during the day (section 1.1). It would seem that people responded to this by no longer using work (even when work continued) as a cue to determine waking and sleeping time, instead presumably deciding based on other factors, perhaps establishing a daily routine independent of work obligations, or by waking and sleeping at different times each day. Days 'off' were no longer days on which a lie in or late night is particularly appropriate.

Analysis of the quantity of sleep showed that the amount of sleep increased in June 2020 only compared to 2016, while the spread of different amounts of sleep increased in June 2020 and remained higher in August 2020. I suggest that this should be linked to the increase in daily routines with a highly disrupted sleep pattern (section 4.4). The nature of the dataset, however, means that it is not possible to discern the extent to which this may be due to each person setting a regular routine which widely diverges between people, or due to each person greatly varying their own sleep pattern.

Wakeup time was further patterned by qualification, which due to the constraints of sample size is described in the large categories of those with a university degree and those without. The differences are partly due to the fact that the less qualified are more likely to have non-standard workdays (section 4.1, cf. Jacobs and Gerson 2004). This is probably the reason for the exception to the general homogeneity of in waking time in August 2020, where the less qualified more often start work very early when working outside the home (while the start times for higher qualified workers working outside the home appear to have shifted later in August 2020 compared to 2016).

On the other hand, non-workday time use is not constrained by the obligations of work, and instead differences in behaviour by qualification level should be explained in terms of a relationship to time use conditioned by early life upbringing (cf. Section 1.3). In 2016, there is a strong difference between degree holders and others on not workdays when out of work: degree holders woke up earlier. In June 2020 and August 2020, however, this gap is no longer present, as those without a degree wake up earlier (supporting the result as regards daily routines in Figure 4.3.3 above). I suggest this may be related either to an effort to put the time to 'good use' by accumulating cultural capital in leisure activities as a response to the uncertainty introduced by lockdown (cf. Section 1.3), or a response to the increased obligations of unpaid housework or childcare (cf. Section 1.2).

Another possible reason is that people wake up early in order to spend time with other family members who wakeup at that time, such as a partner on an early shift. (cf. Section 8, where this question is investigated further). Examination of activities in the two hours after waking suggested that both leisure and unpaid work are roughly equally important activities determining early waking times, while it was not possible to find evidence for a direct link between early wakeup time and time spent with other household members using the indicators considered in section 8.

8 Synchronisation of Routines with Others

The ability – or not – of households to synchronise daily schedules between members is limited by work obligations. When parents' work schedules are out of sync each others' or with the 9 to 5 school day, their work obligations limit the amount of time the family can spend together. Jacobs and Gerson (2004) in the USA and Lesnard (2009) in France have documented this phenomenon, and demonstrated that it is an aspect of class inequality. People in lower qualified occupations are more likely to work non-standard hours, and so parents in those occupations are less likely to have work schedules that match each other's, or school hours which reflect 'standard' 9 to 5 work hours. Presser (2003) documented the negative effects this may have on the parent-child relationship.

In lockdown, however, the loss of work and closure of schools meant, for many, the disappearance of these institutional time constraints. This may have allowed families – and other households – to re-synchronise their daily schedule, and increase the amount of time spent together. Lambert et al. (2020) in France found that people in routine occupations more often reported improved relations with their children during lockdown than higher managerial and professional occupations. They hypothesise that this is because lockdown enabled the synchronisation of daily schedules between family members.

While the dataset used in this study does not contain daily schedules for different members of the same household, making a detailed analysis of 'synchronisation' impossible, it does contain information on time spent with other people, prompted by the question "*Were you alone or with someone else while you were doing this activity?*". Up to four people could be entered for each time slot, creating four 'who-with' vectors. The amount of time spent with other members of the same household can therefore be measured.

It should be noted that the prompt question is ambiguous as to whether a phone call or video-conferencing counts as 'with' someone else. Only 28 diaries had entirely NA values for the first 'who-with' vector, and many of these had non-NA values for the other 'who-with' vectors, suggesting that mistaken entry was at fault rather than true non-response. NA values were therefore counted as 'Alone'.

8.1 Time Spent With Household Members: Class Differences

Figure 8.1.1 shows the average number of hours per day spent with other household members (not limited to family members). Four measures are provided: the number of hours spent together with at least one, two and three other household members, and then 'Person-Hours', a combined measure of people * hours, where one hour spent with two people counts as two hours, as does two hours spent with one person. (Note the variable y-axes.) The figure is subdivided by whether children are present in the household and by four-fold class grouping, the coding of which is described in section 3.3 and Appendix A.

Figure 8.1.1 shows that for respondents with children, there was in many cases an increase in time spent with other household members in June 2020 compared to 2016. There is little to no effect in time spent with 'at least one' other household member, but when 'at least two' is considered there is an increase for many groups over lockdown. This effect is yet more striking in the number of hours spent with three or more family members, which in 2016 is negligible for all groups except 'Intermediate occupations'. Most importantly, the effect is strongly patterned by class; those in 'Routine occupations' spend the least time with other household members in 2016, and show the greatest increase in June 2020, and greatest decline into August 2020. (The large increase for 'at least three' in June 2020 for those not working and with children is not reliable because of under-sampling of this particular group; cf. Figure 8.1.2 below).

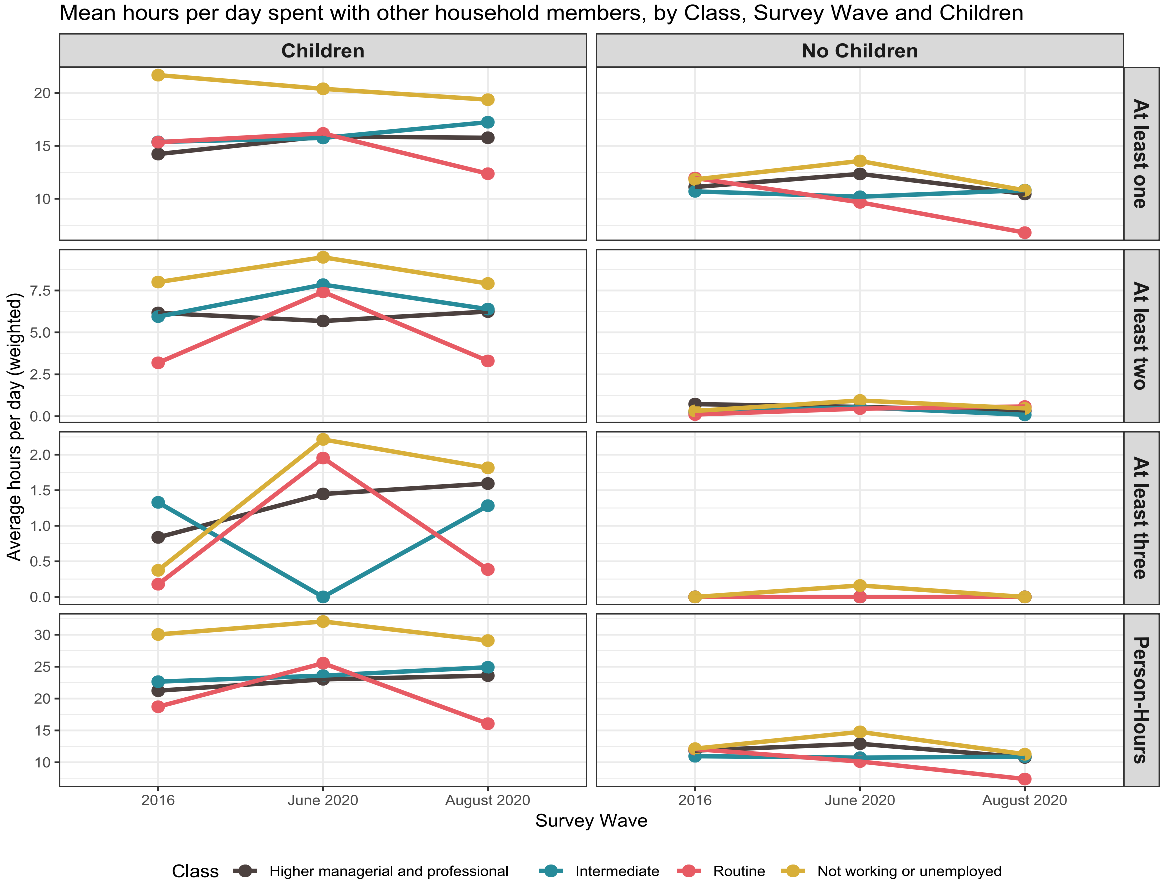

Figure 8.1.1

On the other hand, for respondents without children, there were very few hours spent with more than one other household member, and little change over the survey waves for any measure. The exception is for those in 'Routine' occupations who decrease the number of hours spent with one other household member in June 2020 and even more so in August 2020.

It might be thought useful to take into account here whether the respondent is working, in order to distinguish the effect of the closure of schools from the effect of stopping work in lockdown. The analysis via models accordingly proceeds in two stages. A first model (Model 8.1.1) estimates the change without including work status, so that the effect of reduced work hours in lockdown is included in the difference between survey waves. This shows how the reduction in work and school obligations impacted time spent together with other household members. A second model (Model 8.1.2) then includes work status, in order to estimate the effect of continuing as opposed to stopping work during lockdown.

Of the four indicators shown in Figure 8.1.1, ‘at least two’ was chosen as the outcome variable, since it was taken to correspond most to ‘time together as a family’. ‘At least one’ and ‘person-hours’ are heavily influenced by time with only one other household member, which could be a partner or child but not both. ‘At least two’ gives a better sense of synchronisation of daily routines between multiple household members. Meanwhile ‘at least three’ excludes families with fewer than four members (such as two parents and one child). Model 8.1.1, accordingly, predicts the number of hours spent with at least two family members, in terms of the interaction survey, class and children, including sex and age as control variables. Because the distribution of the outcome variable is irregular, a Gaussian response distribution was used to avoid making inappropriate assumptions.

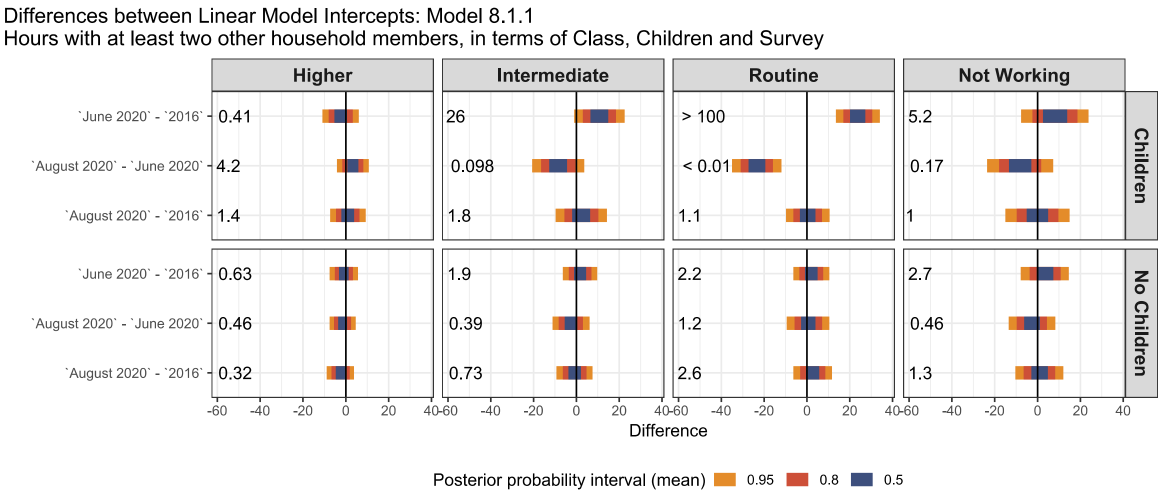

Figure 8.1.2

The results in terms of the difference between survey waves are shown in Figure 8.1.2 (full results are in Appendix C). It can be seen that there is in fact only anecdotal evidence for a difference between survey waves in all categories for respondents without children. Turning to respondents with children, there is a strong pattern for intermediate occupations and (especially) routine occupations. There is strong evidence for an increase in June 2020 compared to 2016 for both these groups, with a credible interval far from 0 at 95%; there is also strong evidence for a decrease for routine occupations, but not intermediate occupations, in August compared to June 2020. Final patterns worth remarking are that among respondents not working or unemployed before lockdown, there is weak to moderate evidence (Bayes factor 5.2) for an increase in time with at least two other household members for those normally unemployed in June 2020 compared to 2016.

Figure 8.1.3 shows the results of Model 8.1.1 in terms of the difference between class groups. This confirms that the dataset supports the inequality of 'family time' between class groups in 2016: while those in 'Higher' and 'Intermediate' occupations with children spend similar quantities of time with at least two other family members, there is extremely strong evidence for a gap between these two groups and 'Routine' occupations, who spend the least time, as well as that those out of work spend more time than those in 'Routine' occupations. In June 2020, however, the increase in this time among those in Routine' occupations has largely removed evidence for this inequality. By August 2020, the 2016 pattern is re-established. In all survey waves, there is only very weak evidence for any class differences among those with children.

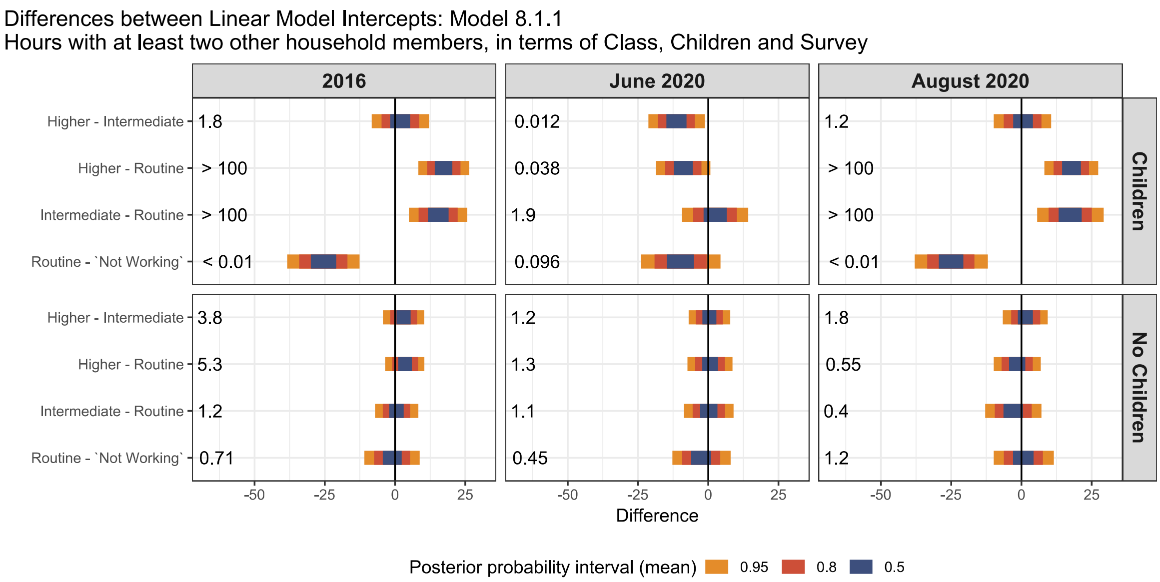

Figure 8.1.3

Model 8.1.2 refits Model 8.1.1, including work status as an interaction predictor, allowing consideration of the impact of stopping work in lockdown on differences between classes. Full results are in Appendix C. Figure 8.1.4 shows the results, in terms of differences between those working and those not. Some values are missing, because the coding of class in questionnaire is unfortunately based on the same variable as employment status for the 2016 wave (see section 3.3 with Appendix A). This means that while in lockdown there are respondents coded as 'Routine' occupations, for instance, but not working because of furlough or unemployment, there are no such respondents in 2016.

Once again, in Figure 8.1.4 there is little evidence for any effect among those without children. Among those with children, however, there is very strong evidence that those in 'Intermediate' occupations spend more time with at least 2 other household members when working than when not in both June 2020 and August 2020, as well as those in 'Higher' occupations in June 2020. This suggests that for these respondents, the presence work schedule in fact counter-intuitively leads to *more* time with other family members, presumably because the schedule is in sync with other household members'. On the other hand, those previously not working (but in work during lockdown) in June 2020 and August 2020, along with 'Higher' and 'Routine' occupations in August 2020 show a pattern where work schedule limits the time spent with other family members, suggesting that work schedules are at least somewhat out of sync. In the specific case of those in routine occupations in lockdown, there is only weak evidence (Bayes factor 4.6) that those out of work increase family time more than those in work, which means that there is only weak evidence for stopping work as a cause for increased family time as a result of 're-synchronisation', as opposed to the closure of schools.

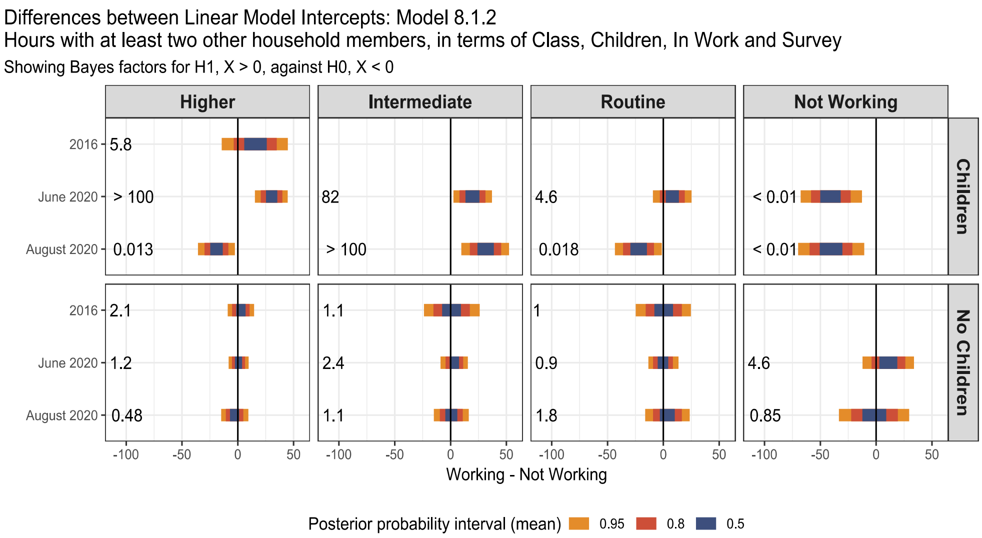

Figure 8.1.4

While in this study the size of the dataset usually makes analysis of the interactions of sex and class impossible to pursue with any confidence, in this case the effects are sufficiently strong, and an analysis incorporating the further variable of sex reveals further patterns. Model 8.1.3 predicts hours spent with at least two other household members, in terms of the interaction of survey wave, children, sex and class, controlling for age group.

Figure 8.1.5

The main results are shown Figure 8.1.5. (full results are in Appendix C). Only values for respondents with children are shown, since (as in the previous models in this section) there is no evidence for any effect in any group of those without children. It can be seen that the pattern among those with ‘Intermediate’ and (especially) ‘Routine’ occupations; an increase in June 2020 compared to 2016, and than a decrease returning to the previous level in August 2020 is similar between women and men. However, the effect appears to be stronger in the case of men. However, in the case of ‘Higher’ occupations, the pattern for men is the inverse of that of women. Women in such occupations spend less time with two or more household members in June 2020 compared to August 2020, while men spend more. The overall pattern for ‘Higher’ occupations (in Figure 8.1.2) is no change. A final result is that the category of men who are not working spent much less time with at least two other household members in August compared to June (and moderate evidence for an increase in June compared to 2020).

Interpreting these results is complex, because while the inequality in time spent with other household members between class groups reflects labour market inequalities, between men and women it not only reflects labour market inequalities but also inequalities in the distribution of childcare-work within the household. It was unfortunately not possible to model this interaction along with the effects of stopping work in lockdown, since the group size becomes too small for the dataset to support inference. I would suggest, however, that the lesser change between survey waves in the case of women compared to men among those in ‘Routine’ occupations may be due to these women taking on a larger proportion of childcare before lockdown, leading to less increase in time with children when work stopped and schools closed. Meanwhile, the decrease in women’s time with other family members in June 2020 compared to 2016 among ‘Higher’ occupations is difficult to account for; it may reflect women in this group passing on a large proportion of childcare onto other household members (in particular, a male partner) in the case of a shift to working from home. This explanation is tenuous however, and further research with a larger dataset is needed.

Overall, because of the limitations of sample size, the level of aggregation of class as well as of the specifics of time use is very broad here. Nevertheless, I wish to suggest that the results support, firstly, the findings of previous research outside the UK (e.g Presser 2003, Jacobs and Gerson 2004, Lesnard 2009) of class inequality in time spent with other household members. Class inequalities in work schedules (cf. Figure 4.1.4) reappear as inequalities in time spent with other household members because work schedules are out of sync with other family members and the school day.

Moreover, the result for June 2020, where this measure for ‘Routine’ occupations, and less so ‘Intermediate’ occupations, increased, bringing all class groups roughly into line, is strong evidence in favour of the hypothesis of Lambert et al. (2020), that lockdown allowed families whose time together had been limited by non-standard work schedules to re-synchronise their daily schedules and spend more time together. Because the effect is observable only among respondents with children, for both those who continue working and those who do not during lockdown, it would seem that the principal cause is the closure of schools; there is only weak evidence that stopping work in lockdown was a factor, perhaps because of the large number of respondents who continued to work. It would seem, therefore, that the *anomie* of time use created by the reduction of institutional time obligations in lockdown allowed families, in particular working-class families, to spend more time together. This evened out class inequalities in this regard, something which did not, however, survive the re-opening of schools and partial return to work in August 2020.

There is some evidence that the pattern is stronger for men than women, which may reflect pre-lockdown inequalities in the distribution of childcare. There are also effects that are harder to explain, among 'Higher' and 'Intermediate' occupations: women in 'Higher' occupations spending far less time with multiple other household members in June 2020 compared to 2016, and people in 'Higher' and 'Intermediate' occupations spending more time with other household members when working than when not working. I suggest that these may reflect, firstly, a redistribution of childcare responsibilities within the household among those in 'Higher' occupations, and secondly, the effect of workday routine *maintaining* synchronised family life among those with 'standard' pre-lockdown work schedules. These explanations are necessarily highly provisional, however.

Conclusion

The first UK lockdown in the spring and summer of 2020 enormously disrupted everyday life. A large range of daily activities, from socialising outside the home to exercise to school, and, for many, work, became off limits. As argued above (section 1.1) the fact that many activities were no longer obligatory, or even possible, broke up daily routines and freed up time in the day, which created a situation of *anomie* as regards everyday time use: a lack of applicability of pre-existing social norms.

The dataset used is taken from the *United Kingdom Time Use Survey Sequence Pre and During COVID-19 Social Restrictions, 2016-2020* (Gershuny and Sullivan 2021), including individuals aged 18-65, and excluding students. It is a three-wave (not longitudinal) time diary study, with a total sample size of 2583 time diaries, analysed in such a way as to approach representation of the wider UK population. The three waves were in 2016, a pre-lockdown reference; June 2020, during widespread national restrictions and just as schools began to reopen; and August 2020, a period when restrictions were almost entirely relaxed, and only maintained for large outdoor gatherings (see section 2).

This study has sought to illuminate how people responded to this situation of *anomie* in terms of time use, as regards their daily routines, the fragmentation of time, their pattern of leisure activities, times of waking and sleeping, and spending time with other household members. Since time use is found at the intersection of many domains of social behaviour – work, leisure, family, friends – many factors drive behaviour in complex combinations. It was suggested (in sections 1.2 and 1.3) that these factors can be grouped into two broad categories: firstly, the effect of shifting time obligations, as regards paid work, housework and childcare; and secondly, the spending free time in leisure activities, which can be seen as a cultural practice largely conditioned by early-life upbringing, or as an active attempt to accumulate cultural capital. The analysis has necessarily proceeded in terms of separate features of time use, and each analysis section has seen these factors acting in combination.

Obligations on time are principally visible as regards housework. This was investigated through the perspectives of daily routines, and the fragmentation of the day into different daily activities. Lockdown led to an increase in non-workdays for both men and women. Men's presence in the home, whether working or not, has led to them having more daily routines filled with a sort of 'workday' of housework or childcare; while women also increased this form of daily routine, the inequality between men and women decreased. Men's non-workdays are more likely to be filled with almost uninterrupted leisure activities, or be entirely devoted to an unpaid workday. Women, on the other hand, were more likely to have a day of leisure constantly interrupted with unpaid work, or to apparently schedule the unpaid work into a single period, whether morning, midday or afternoon. The latter, in particular a lie-in followed by a period of unpaid work around midday (cluster 32 in Figure 4.2.1), is particularly typical of women who stopped working during lockdown.

When the number of activities is considered, the only change found was an increase in activities for women without children, and men with children, in August 2020 only. It was surmised (without the possibility of confirming the result with the dataset available) that this reflects increased housework work burden on one partner when the other returns to work. Childcare, meanwhile, appears to have increased not so much the number of activities on the primary activity vector but the amount of time entered on the secondary activity vector, for both men and women in June 2020 only.

Male-female inequality during lockdown in terms of housework is therefore visible more in terms of the fragmentation of routines than in the number of days primarily devoted to unpaid work. Men's increased presence in the home during lockdown increased the number of days they devoted in great or small part to unpaid housework, decreasing the male-female inequality in this regard; male-female inequalities during lockdown appear larger when the fragmentation of time into activity periods. Meanwhile inequalities in time spent on, recorded mostly in terms of 'multitasking', temporarily decreased during lockdown. This result is in line with previous research (Sullivan 1997, Sevilla et al. 2012, Sullivan and Gershuny 2018) as well as the lockdown study of Sevilla et al. (2020) that identify time fragmentation as a key dimension of male-female time inequality. It was not possible from the dataset to look at the shared burden between members of a couple; this has been identified as a key factor in time spent on housework and childcare (Sullivan 1997), and may explain some of the more puzzling results identified here. Further research should use surveys that allow taking this factor into account (if available for the period of lockdown).

Moving from housework to paid work, there is no evidence in the dataset that the decrease in work during lockdown differentially affected standard, ‘9 to 5’ workdays as opposed to shift work. Two key trends are nevertheless apparent. Lockdown decreased the well-known class inequality where less qualified workers are more likely to work non-standard work schedules (Presser 2003, Jacobs and Gerson 2004, Lesnard 2009), as higher qualified workers working from home took advantage of decreased employer control over their time to shift to an afternoon work pattern. This trend however decreased as restrictions ended, but high rates of working from home continued, in August 2020. The decrease may have been due to employer control of work time, or employees reacting to the *anomie* as regards work time by reclaiming previous habits of daily routine. A second pattern is that very long workdays with little leisure time greatly increase during lockdown, an increase that continues into the August 2020 survey wave. Once again, it has not been possible to distinguish whether this is due to increased employer demands, perhaps on ‘essential workers’, or is due to workers’ behaviour in *anomie* as work overflows the boundaries of pre-lockdown daily routine. It would be very useful for further research if extent to which workers have control over work schedules – and the internal content of such schedules – were included in future waves of the survey.

Analysis of leisure activities shows patterns in how people spent their free time. ‘Voracity’ of leisure, the number of different leisure activities performed (an analogue to Peterson’s (1992) ‘omnivorousness’), is strongly linked to educational level before and during lockdown, following the previous results of Southerton (2006) and Sullivan and Katz-Gerro (2007). In June 2020, degree holders decreased their voracity, a result that suggests high voracity among the highly educated before lockdown is the result of the ‘harried leisure class’ (Linder 1971, Gershuny 2005) attempting to accumulate varied cultural capital in the brief time available; lockdown appears to have decreased pressure for social competition in this regard. In August 2020, however, degree holders – but only those who remained not working – increased the voracity of their leisure consumption, suggesting an attempt to put the *anomie* of their unemployment or furlough to use.

Meanwhile, the proportion of leisure time in the consumption of electronic media (such as videos, TV and music) is similarly patterned by educational level, with the more educated spending less. It increased among the less educated during lockdown, and greatly decreased in August 2020 for the less educated who did not return to work. The decrease among the less educated in August 2020 may relate to increased engagement in forms of leisure seen as higher status or more productive.

Another aspect of time use that appears patterned by educational level is the time of waking. Before lockdown, there is a large gap on non-workdays when out of work between the less educated, who wake up much later than the more educated. This gap vanishes during lockdown as the less educated wake up much earlier, and the new pattern is maintained into 2020. This may be because of a desire to 'get the most' out of the day, putting the time to use; or because of the global elimination of differences wakeup times on workdays and non-workdays (see below); or the synchronisation of daily schedules between family members (although no direct link to the latter was found).

The results concerning leisure time suggest that multiple aspects of time use are patterned according to qualification, in such a way that suggests they can be seen as cultural practices which are determined by early life upbringing and whose transmission between generations forms part of the reproduction of social class (section 1.3). This cause of time use appears to be an important explanatory factor in patterns of time use in *anomie* when the constraints of social norms and daily schedule become less important. Moreover, there is some indication that this reaction was not deterministic, straightforwardly in line with qualification level, but that less qualified respondents in certain conditions put their free time 'to good use' in ways that may imply an attempt to imitate norms of 'productive' leisure typical of the more qualified. This interpretation, of course, assumes that norms of 'useful' or 'productive' leisure are applicable, which would need confirmation by more qualitative studies. The results here, along with the detailed (but not time-use) French study of Jonchery and Lombardo (2020), indicate that this may be a fruitful direction for further research.

The synchronisation of daily schedules between family members is an aspect of time use that appears to be a key aspect of the working-class reaction to the *anomie* created by the loss of work time and closure of schools. While the results for 2016 confirm the known inequality whereby the increased likelihood of shift-work among less qualified workers translates into less time spent together as a family, because of the de-synchronisation of daily schedules (Jacobs and Gerson 2004, Lesnard 2009), Lambert et al. (2020) hypothesised that lockdown allowed working class families to spend more time with other household members. The results here support that hypothesis, and show that there was a large – but temporary, vanishing in August 2020 – increase in the time respondents in specifically 'routine' occupations spent with other household members, when living with children. It appears that this effect is mostly due to the closure of schools, and there is only weak evidence that stopping work is also a factor.

Changes to sleep patterns also appear during lockdown. While not unknown in 2016, days in which sleep patterns are very far removed from the norm greatly increase. This is especially the case for men, perhaps because their time is often less constrained by the demands of housework and childcare. The result is however, firstly only the case for daily routines in which sleep pattern diverges most widely from the norm, and secondly is still the case only of a small minority of respondents. As such, it appears to represent a particular and minority response to *anomie* of time use. The increase in these schedules appears to have contributed to an increase in the spread of the number of daily activities as well as total sleep time, an increase that continues into August 2020.

A change to waking and sleeping that is more generalised is the elimination of differences in waking and sleeping time between workdays and non-workdays in lockdown, a pattern which continues into August 2020. While non-workdays in the 2016 wave are characterised by a lie-in and a high percentage of very late nights, in the 2020 survey waves people wake up earlier and go to sleep earlier on non-workdays, while on workdays they wake up later and have a higher percentage of late nights. The result is that the distinction between the workdays and non-workdays in terms of sleep pattern becomes statistically almost imperceptible (except for workers on early morning shifts). It would seem that the disruption to the working week during lockdown led to people establishing sleeping and waking schedules irrespective of working, which may have led to a conceptual blurring of 'days on' and 'days off'. This is a major societal behavioural change, which may have far reaching consequences for perceptions of work-life balance.

A final set of results look at the relationship of certain indicators to a subjective assessment of mental health in lockdown, controlling for the impact of stopping work. Less clearly structured daily routines – non standard workdays, highly shifted sleep patterns, and most of all, doing housework as a fragmented day rather than in a single block of time – are associated with worse mental health during lockdown. It would seem that maintaining a measure of scheduling or daily routine as 'resistance' to the *anomie* in lockdown is associated with better mental health, in what is probably a two-way causal relationship. Days with a high level of completion on the secondary activity vector are also associated with worse mental health, perhaps reflecting the stress of increased disruption, if this is not another aspect of a disordered daily routine. Meanwhile, a higher proportion of leisure time spent in the consumption of electronic media is linked to better mental health during lockdown, perhaps pointing to beneficial mental health effects of less demanding or more passive leisure activities. While the mental health indicator in the questionnaire is subjective and, as often in such questionnaires, far inferior to more objective assessments, the results indicate directions for further research.

Overall, the multifaceted results indicate the complex impact of lockdown on daily routines and time use. Some patterns appear the result of shifting obligations on time, whether in the form of paid work or housework; many, however, are best explained in terms of people maintaining structured daily routine, or failing to do so, in the face of *anomie*, the sudden lack of applicability of previous norms of daily time use in lockdown. These reactions are often patterned by educational level and social class, supporting a perspective that sees use of free time as a cultural practice. Many of the patterns observed, in particular the increase of very long workdays, the increase in intense leisure consumption among those out of work, and the lack of distinction between sleep patterns on workdays and non-workdays, persist or even strengthen in the August 2020 survey wave: it would seem that the experience of lockdown in the first half of 2020 may have had long-term effects on time use that will outlast the relaxing of restrictions.

References

Academic Works

Abbott, Andrew 1995. ‘Sequence Analysis: New Methods for Old Ideas’. *Annual Review of Sociology* 21: 93–113.

Abbott, Andrew, and Angela Tsay 2000. ‘Sequence Analysis and Optimal Matching Methods in Sociology: Review and Prospect’. *Sociological Methods & Research* 29(1): 3–33.

Adorno, Theodor [1977] 2001. ‘Free Time’. pp. 187–97 in *The Culture Industry*, edited by J. M. Bernstein. London: Routledge.

Aisenbrey, Silke, and Anette E. Fasang 2010. ‘New Life for Old Ideas: The “Second Wave” of Sequence Analysis Bringing the “Course” Back Into the Life Course’. *Sociological Methods & Research* 38(3): 420–62.

Andraszewicz, Sandra, Benjamin Scheibehenne, Jörg Rieskamp, Raoul Grasman, Josine Verhagen, and Eric-Jan Wagenmakers 2015. ‘An Introduction to Bayesian Hypothesis Testing for Management Research’. *Journal of Management* 41(2): 521–43.

As, Dagfinn 1978. ‘Studies of Time-Use: Problems and Prospects’. *Acta Sociologica* 21(2): 125–41.

Beck, Ulrich 1992. *Risk Society: Towards a New Modernity*. London: Sage Publications.

Belbin, Lee, Daniel P. Faith, and Glenn W. Milligan 1992. ‘A Comparison of Two Approaches to Beta-Flexible Clustering’. *Multivariate Behavioral Research* 27(3): 417–33.

Besnard, Philippe 1983. ‘Le destin de l’anomie dans la sociologie du suicide’. *Revue Française de Sociologie* 24(4): 605–29.

Besnard, Philippe 1993. ‘Anomie and Fatalism in Durkheim’s Theory of Regulation’. pp. 164–83 in *Emile Durkheim: Sociologist and moralist*, edited by S. P. Turner. London; New York (N. Y.): Routledge.

Bidart, Claire, Alain Degenne, and Michel Grossetti 2011. *La Vie En Réseau: Dynamique Des Relations Sociales*. Paris: Presses universitaires de France.

Binkley, Sam 2009. ‘Governmentality, Temporality and Practice: From the Individualization of Risk to the `contradictory Movements of the Soul’’. *Time & Society* 18(1): 86–105.

Bittman, Michael, and Judy Wajcman 2000. ‘The Rush Hour: The Character of Leisure Time and Gender Equity’. *Social Forces* 79(1): 165–89.

Blundell, Richard, Monica Costa Dias, Robert Joyce, and Xiaowei Xu 2020. ‘COVID-19 and Inequalities’. *Fiscal Studies* 41(2): 291–319.

Bouffartigue, Paul 2006. ‘La division sexuée du travail professionnel et domestique : quelques remarques pour une perspective temporelle’. *Lien social et Politiques* (54): 13–23.

Bourdieu, Pierre 1979. *La Distinction: critique sociale du jugement*. Paris: Les Éditions de Minuit.

Bourdieu, Pierre 2003. ‘L’être social, le temps et le sens de l’existence’. in *Méditations pascaliennes*, *Essais*. Paris: Seuil.

Brewer, Mike, Nye Cominetti, Kathleen Henehan, Charlie McCurdy, Rukmen Sehmi, and Hannah Slaughter 2020. *Jobs, Jobs, Jobs: Evaluating the Effects of the Current Economic Crisis on the UK Labour Market*. Resolution Foundation.

Burgard, Sarah A., and Jennifer A. Ailshire 2013. ‘Gender and Time for Sleep among U.S. Adults’. *American Sociological Review* 78(1): 51–69.

Chatzitheochari, Stella, and Sara Arber 2009. ‘Lack of Sleep, Work and the Long Hours Culture: Evidence from the UK Time Use Survey’. *Work, Employment and Society* 23(1): 30–48.

Chenu, Alain, and Laurent Lesnard 2006. ‘Time Use Surveys: A Review of Their Aims, Methods, and Results’. *European Journal of Sociology* 47(3): 335–59.

Chenu, Alain, and J. P. Robinson 2002. ‘Synchronicity in the Work Schedules of Working Couples’. *Monthly Labor Review* 125(4): 55–63.

Cominetti, Nye, Laura Gardiner, and Hannah Slaughter 2020. *The Full Monty: Facing up to the Challenge of the Coronavirus Labour Market Crisis*. Resolution Foundation.

Cominetti, Nye, Kathleen Henehan, Hannah Slaughter, and Greg Thwaites 2021. *Long Covid in the Labour Market: The Impact on the Labour Market of Covid-19 a Year into the Crisis, and How to Secure a Strong Recovery*. Resolution Foundation.

Cornwell, Benjamin, Jonathan Gershuny, and Oriel Sullivan 2019. ‘The Social Structure of Time: Emerging Trends and New Directions’. *Annual Review of Sociology* 45(1): 301–20.

Coulangeon, Philippe 2010. ‘Les métamorphoses de la légitimité: Classes sociales et goût musical en France, 1973-2008’. *Actes de la recherche en sciences sociales* 181–182(1): 88–105.

Darmon, Muriel, Delphine Dulong, and Elsa Favier 2019. ‘Temps et pouvoir’. *Actes de la recherche en sciences sociales* 226–227: 6–15.

Durkheim, Émile 1897. *Le Suicide*. Paris: Ancienne Librarie Germer Ballière.

Foucault, Michel 2004. *Naissance de La Biopolitique: Cours Au Collège de France, 1978-1979*. edited by F. Ewald, A. Fontana, and M. Senellart. Paris: Gallimard : Seuil.

Gershuny, J., and O. Sullivan 1998. 'The Sociological Uses of Time-Use Diary Analysis'. *European Sociological Review* 14(1): 69–85.

Gershuny, J., and O. Sullivan 2021. 'United Kingdom Time Use Survey Sequence Pre and During COVID-19 Social Restrictions, 2016-2020'.

Gershuny, Jonathan 2005. 'Busyness as the Badge of Honor for the New Superordinate Working Class'. *Social Research* 72(2): 287–314.

Gershuny, Jonathan, Oriel Sullivan, Almudena Sevilla, Marga Vega-Rapun, Francesca Foliano, Juana Lamote de Grignon, Teresa Harms, and Pierre Walthery 2020. *A New Perspective from Time Use Research on the Effects of Lockdown on COVID-19 Behavioral Infection Risk. preprint*. SocArXiv.

Giddens, Anthony 1991. *Modernity and Self-Identity: Self and Society in the Late Modern Age*. Reprint. Cambridge: Polity Press.

Goldthorpe, John H. 1980. *Social Mobility and Class Structure in Modern Britain*. Oxford: Clarendon Press.

Grignon, Claude, and Jean-Claude Passeron 2015. *Le savant et le populaire: misérabilisme et populisme en sociologie et en littérature*. Paris: Éd. du Seuil.

Gunter, B. C., and Nancy C. Gunter 1980. 'Leisure Styles: A Conceptual Framework for Modem Leisure'. *Sociological Quarterly* 21(3): 361–74.

Hammer, Bernhard 2012. 'Statistical Models for Time Use Data: An Application to Housework and Childcare Activities Using the Austrian Time Use Surveys from 2008 and 1992'. Masters Thesis, Universitat Wien, Vienna, Austria.

Han, Byung-Chul [2010] 2015. *The Burnout Society*. Stanford, California: Stanford Briefs.

Hays, Sharon 1996. *The Cultural Contradictions of Motherhood*. New Haven, Conn.: Yale Univ. Press.

Henri-Panabière, Gaële, Martine Court, Julien Bertrand, Géraldine Bois, and Olivier Vanhée 2019. 'La montre et le martinet: Structuration temporelle de la vie familiale et inégalités scolaires'. *Actes de la recherche en sciences sociales* N°226-227(1): 16–30.

Héran, François 1988. 'La sociabilité, une pratique culturelle'. *Economie et statistique* 216(1): 3–22.

Hislop, Jenny, and Sara Arber 2003. 'Sleepers Wake! The Gendered Nature of Sleep Disruption among Mid-Life Women'. *Sociology* 37(4): 695–711.

Jacobs, Jerry A., and Kathleen Gerson 2004. *The Time Divide: Work, Family, and Gender Inequality*. Cambridge, MA: Harvard University Press.

Javeau, Claude 1983. ‘Comptes et mécomptes du temps’. *Cahiers Internationaux de Sociologie* 74: 71–82.

Jonchery, Anne, and Philippe Lombardo 2020. *Pratiques culturelles en temps de confinement*. Ministère de la Culture.

Kalleberg, Arne L. 2011. *Good Jobs, Bad Jobs: The Rise of Polarized and Precarious Employment Systems in the United States, 1970s to 2000s*. New York: Russell Sage Foundation.

Lambert, Anne, Joanie Cayouette-Remblière, Élie Guéraut, Guillaume Le Roux, Catherine Bonvalet, Violaine Girard, and Laetitia Langlois 2020. ‘Le travail et ses amenagements : ce que la pandemie de covid-19 a change pour les Francais’. *Population & Sociétés* 579: 1–4.

Lareau, Annette 2003. *Unequal Childhoods: Class, Race, and Family Life*. Berkeley: University of California Press.

Lazarsfeld, Paul Felix, Marie Jahoda, and Hans Zeisel 1981. *Les Chômeurs de Marienthal*. Paris: Les Editions de Minuit.

Lefebvre, Henri 1958. *Critique de La Vie Quotidienne*. Vol. 1. Introduction. 2nd ed. Paris: L’Arche Editeur.

Lefebvre, Henri 1992. *Éléments de Rythmanalyse*. Paris: Éditions Syllepse.

Lefebvre, Henri n.d. ‘Quotidienneté’. *Encyclopædia Universalis*.

Lesnard, Laurent 2004. ‘Schedules as Sequences: A New Method to Analyze the Use of Time Based on Collective Rhythm with an Application to the Work Arrangements of French Dual-Earner Couples’. *Electronic International Journal of Time Use Research* 1(1): 60–84.

Lesnard, Laurent 2008. ‘Off-Scheduling within Dual-Earner Couples: An Unequal and Negative Externality for Family Time’. *American Journal of Sociology* 114(2): 447–90.

Lesnard, Laurent 2009. *La famille désarticulée. Les nouvelles contraintes de l’emploi du temps*. Paris cedex 14: Presses Universitaires de France.

Lesnard, Laurent 2010. ‘Setting Cost in Optimal Matching to Uncover Contemporaneous Socio-Temporal Patterns’. *Sociological Methods & Research* 38(3): 389–419.

Lesnard, Laurent 2014. ‘Using Optimal Matching Analysis in Sociology: Cost Setting and Sociology of Time’. pp. 39–50 in *Advances in Sequence Analysis: Theory, Method, Applications*. Vol. 2, *Life Course Research and Social Policies*, edited by P. Blanchard, F. Bühlmann, and J.-A. Gauthier. Cham: Springer International Publishing.

Lesnard, Laurent, and Man Yee Kan 2011. ‘Investigating Scheduling of Work: A Two-Stage Optimal Matching Analysis of Workdays and Workweeks: Investigating Scheduling of Work’. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 174(2): 349–68.

Linder, Staffan Burenstam 1971. *The Harried Leisure Class*. New York: Columbia University Press

Masclet, Olivier 2018. *L’invité permanent: la réception de la télévision dans les familles populaires*. Paris: Armand Colin.

Mattingly, M. J., and S. M. Blanchi 2003. ‘Gender Differences in the Quantity and Quality of Free Time: The U.S. Experience’. *Social Forces* 81(3): 999–1030.

Maume, David J., Rachel A. Sebastian, and Anthony R. Bardo 2010. ‘Gender, Work-Family Responsibilities, and Sleep’. *Gender & Society* 24(6): 746–68.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook 2001. ‘Birds of a Feather: Homophily in Social Networks’. *Annual Review of Sociology* 27(1): 415–44.

Merton, Robert King 1968. ‘Continuities in the Theory of Social Structure and Anomie’. pp. 161–94 in *Social theory and social structure*. New York, NY: Free Press.

Millet, Mathias, and Daniel Thin 2005. ‘Le temps des familles populaires à l’épreuve de la précarité’. *Lien social et Politiques* (54): 153–62.

Nandi, Alita, and Lucinda Platt 2020. ‘Ethnic Differences in the Effects of Covid-19: Household and Local Context’.

National Readership Survey n.d. ‘Social Grade’. Retrieved 19 May 2021 (http://www.nrs.co.uk/nrs-print/lifestyle-and-classification-data/social-grade/).

Niemi, Iiris 1993. ‘Systematic Error in Behavioural Measurement: Comparing Results from Interview and Time Budget Studies’. *Social Indicators Research* 30(2–3): 229–44.

Office for National Statistics 2021. ‘Employment, Unemployment and Economic Inactivity by Age Group (Seasonally Adjusted)’.

Pailhé, Ariane, Anne Solaz, and Maria Stanfors 2020. ‘The Great Convergence? Gender and Unpaid Work in Europe and the United States’. *Lund Papers in Economic Demography* (1): 63.

Paugam, Serge [1991] 2009. *La disqualification sociale. Essai sur la nouvelle pauvreté*. Paris cedex 14: Presses Universitaires de France.

Petersen, Anne Helen 2020. *Can’t Even: How Millennials Became the Burnout Generation*. Boston: Houghton Mifflin Harcourt.

Peterson, Richard A. 1992. ‘Understanding Audience Segmentation: From Elite and Mass to Omnivore and Univore’. *Poetics* 21(4): 243–58.

Presser, Harriet B. 2003. *Working in a 24/7 Economy: Challenges for American Families*. New York, NY: Russell Sage Foundation.

Public Health England n.d. *COVID-19: Mental Health and Wellbeing Surveillance Report*. Public Health England.

Robette, Nicolas, and Olivier Roueff 2017. 'L'espace contemporain des goûts culturels: Homologies structurales entre domaines de pratiques et entre classes sociales'. *Sociologie* 8(4): 369–94.

Rosa, Hartmut [2005] 2013. *Social Acceleration: A New Theory of Modernity*. New York: Columbia University Press.

Sevilla, Almudena, Jose I. Gimenez-Nadal, and Jonathan Gershuny 2012. 'Leisure Inequality in the United States: 1965–2003'. *Demography* 49(3): 939–64.

Sevilla, Almudena, Angus Phimister, Sonya Krutikova, Lucy Kraftman, Christine Farquharson, Monica Costa Dias, Sarah Cattan, and Alison Andrew 2020. *How Are Mothers and Fathers Balancing Work and Family under Lockdown? IFS Briefing Note*. BN290.

Southerton, Dale 2006. 'Analysing the Temporal Organization of Daily Life: Social Constraints, Practices and Their Allocation'. *Sociology* 40(3): 435–54.

Studer, Matthias, and Gilbert Ritschard 2016. 'What Matters in Differences between Life Trajectories: A Comparative Review of Sequence Dissimilarity Measures'. *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 179(2): 481–511.

Sullivan, O., and J. Gershuny 2015. 'United Kingdom Time Use Survey, 2014-2015'.

Sullivan, O., and T. Katz-Gerro 2007. 'The Omnivore Thesis Revisited: Voracious Cultural Consumers'. *European Sociological Review* 23(2): 123–37.

Sullivan, Oriel 1997. 'Time Waits for No Woman'. *Sociology* 31(2): 221–39.

Sullivan, Oriel, and Jonathan Gershuny 2018. 'Speed-Up Society? Evidence from the UK 2000 and 2015 Time Use Diary Surveys'. *Sociology* 52(1): 20–38.

Sullivan, Oriel, Jonathan Gershuny, Almudena Sevilla, Pierre Walthery, and Marga Vega-Rapun 2020. 'Time Use Diary Design for Our Times - an Overview, Presenting a Click-and-Drag Diary Instrument (CaDDI) for Online Application'. *Journal of Time Use Research* 1–17.

Szalai, Alexander, ed. 1972. *The Use of Time: Daily Activities of Urban and Suburban Populations in Twelve Countries*. The Hague: Mouton.

Vagni, Giacomo, and Benjamin Cornwell 2018. 'Patterns of Everyday Activities across Social Contexts'. *Proceedings of the National Academy of Sciences* 115(24): 6183–88.

Wilensky, Harold 1963. ‘The Uneven Distribution of Leisure’. pp. 107–45 in *Work and Leisure*, edited by E. O. Smigel. New Haven: College and University Press.

Winship, Christopher, and Larry Radbill 1994. ‘Sampling Weights and Regression Analysis’. *Sociological Methods & Research* 23(2): 230–57.

Young, Rebekah, and David R. Johnson 2010. ‘To Weight or Not to Weight, That Is the Question: Survey Weights in Family Research’.

Software

Bürkner, Paul-Christian. 2017. ‘Brms: An R Package for Bayesian Multilevel Models Using Stan’. *Journal of Statistical Software* 80(1): 1–28.

Carpenter, Bob et al. 2017. ‘Stan : A Probabilistic Programming Language’. *Journal of Statistical Software* 76(1). http://www.jstatsoft.org/v76/i01/ (August 23, 2020).

Gabadinho, Alexis, Gilbert Ritschard, Nicolas S. Müller, and Matthias Studer. 2011. ‘Analyzing and Visualizing State Sequences in R with TraMineR’. *Journal of Statistical Software* 40(4). http://www.jstatsoft.org/v40/i04/ (June 6, 2021).

Galili, Tal. 2015. ‘Dendextend: An R Package for Visualizing, Adjusting and Comparing Trees of Hierarchical Clustering’. *Bioinformatics* 31(22): 3718–20.

Grolemund, Garrett, and Hadley Wickham. 2011. ‘Dates and Times Made Easy with Lubridate’. *Journal of Statistical Software* 40(3): 1–25.

Henderson, Ewen. 2020. *Ghibli: Studio Ghibli Colour Palettes*. . R. https://CRAN.R-project.org/package=ghibli.

Kay, Matthew. 2020. *Tidybayes: Tidy Data and ‘Geoms’ for Bayesian Models*.

———. 2021. *Ggdist: Visualizations of Distributions and Uncertainty*. Zenodo. https://zenodo.org/record/3879620 (June 6, 2021).

Maechler, Martin, Peter Rousseeuw, Anja Struyf, and Mia Hubert. 2021. *Cluster: ‘Finding Groups in Data’: Cluster Analysis Extended*. https://svn.r-project.org/R-packages/trunk/cluster/.

Oehm, Daniel. 2021. *EvoPalette*. https://github.com/doehm/evoPalette.

R Core Team. 2021. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Spinu, Vitalie, Garrett Grolemund, and Hadley Wickham. 2018. *Lubridate: Make Dealing with Dates a Little Easier*. https://CRAN.R-project.org/package=lubridate.

Wickham, Hadley et al. 2019. ‘Welcome to the Tidyverse’. *Journal of Open Source Software* 4(43): 1686-1692.

Wickham, Hadley, and Evan Miller. 2020. *Haven: Import and Export ‘SPSS’, ‘Stata’ and ‘SAS’ Files*. https://CRAN.R-project.org/package=haven.

Wickham, Hadley, and Dana Seidel. 2019. *Scales: Scale Functions for Visualization*. https://CRAN.R-project.org/package=scales.

Xie, Yihui. 2014. *Knitr: A Comprehensive Tool for Reproducible Research in R*. Chapman and Hall/CRC. http://www.crcpress.com/product/isbn/9781466561595.

Zeileis, Achim et al. 2019. *Colorspace: A Toolbox for Manipulating and Assessing Colors and Palettes*. arXiv.org E-Print Archive. arXiv. http://arxiv.org/abs/1903.06490.

Appendices

Appendix A

Survey questions from which variables were derived (see section 3.3). Information about the prompt questions for the diary data entries can be found in Sullivan et al. (2020).

SEX
Are you:
1. Male
2. Female

NUNDER5, N5TO11, N12TO16
How many children of the following ages live in your household?
1. Aged under 5 [open box: 0-99]
2. Aged 5 to 11 [open box: 0-99]
3. Aged 12 to 16 [open box: 0-99]

HIED
What is the highest level of education attainment or training you have successfully completed?
1. No qualifications
2. GCSEs
3. A Levels or equivalent (UK)
4. Apprenticeship
5. First degree/ undergraduate degree or equivalent
6. Higher degree or equivalent

DAGEGRP
How old are you?
1. <18 (*leading to termination of the questionnaire*)
2. 18-24
3. 25-34
4. 35-44
5. 45-54
6. 55-64
7. 65+

ECONSTAT
Which of these best describes your occupation?
1. Self-employed with no employees
2. Self-employed with 1-25 employees
3. Employed
4. Partner/director/owner company of 25+employees
5. Student

6. Casual worker – not in permanent employment
7. Housewife/ Homemaker
8. Retired and living on state pension
9. Retired and NOT living on state pension
10. Unemployed or not working due to long-term sickness
11. Full-time carer of other household member

DCLASUK

Please indicate to which occupational group YOU belong, or which group fits YOU best.

1. Semi or unskilled manual work (e.g. Manual workers, all apprentices to be skilled trades, Caretaker, Park keeper, non-HGV driver, shop assistant)
2. Skilled manual worker (e.g. Skilled Bricklayer, Carpenter, Plumber, Painter, Bus/ Ambulance Driver, HGV driver, AA patrolman, pub/bar worker, etc.)
3. Clerical / administrative NOT with managerial or supervisory responsibility (e.g. Office worker, salesperson, etc.)
4. Supervisory/ junior managerial (e.g. retail manager, foreman with 25+ employees)
5. Intermediate managerial/ professional/ administrative (e.g. Newly qualified (under 3 years) doctor, Solicitor, Board director small organisation, middle manager in large organisation, principle officer in civil service/local government)
6. Higher managerial/ professional/ administrative (e.g. Established doctor, Solicitor, Board Director in a large organisation (200+ employees, top level civil servant/public service employee)

Answers 1-2 were coded as 'Routine and manual occupations', 3 as 'Intermediate occupations', 4-6 as 'Higher managerial, administrative and professional occupations'. These were then combined with the responses from ECONSTAT (above), with ECONSTAT taking precedence over this question in case of a clash. Answers 1 and 2 from ECONSTAT (self-employed) were added to 'Intermediate occupations', answer 5 (Student) to 'Student', answer 6 (Casual Worker) to 'Routine and Manual occupations', and answers 7-11 to 'Not working, never worked and long-term unemployed'.

EMPLNOW

Which of the following best describes how you are working now?

1. I am working full time, travelling to my place of work
2. I am working part time, travelling to my place of work
3. I am working full time, usually working from home
4. I am working part time, usually working from home
5. I have been furloughed by my employer
6. I'm not working - I am between jobs, unemployed
7. I'm not working - on parental leave
8. I'm not working - I am a homemaker
9. I'm not working - I am studying
10. I'm not working - retired
98. Other

<u>Mental Health Questionnaire:</u>

NQ1. Have you recently been able to concentrate on what you're doing?
NQ2. Have you recently lost much sleep over worry?

NQ3. Have you recently felt you were playing a useful part in things?
NQ4. Have you recently felt capable of making decisions about things?
NQ5. Have you recently felt constantly under strain?
NQ6. Have you recently felt you couldn't overcome your difficulties?
NQ7. Have you recently been able to enjoy your normal day-to-day activities?
NQ8. Have you recently been able to face up to your problems?
NQ9. Have you recently been feeling unhappy and depressed?
NQ10. Have you recently been losing confidence in yourself?
NQ11. Have you recently been thinking of yourself as a worthless person?
NQ12. Have you recently been feeling reasonably happy, all things considered?

Each question offers the same four responses (with 'more' and 'less' inverted for questions 1, 3, 4, 7, 8, 12 so that options three and four always imply worse mental health):

1. Less so than usual
2. Same as usual
3. More so than usual
4. Much more than usual

Appendix B

Indicating the recoding of questionnaire activity codes: see section 3.1.

Original Code	**5 -way Activity Group**
Sleeping	rest
Resting	rest
Washing, dressing	rest
Eating, drinking,home or work	rest
Preparing food, cooking etc	unpaid_work
Cleaning tidying housework	unpaid_work
Clothes washing, mending	unpaid_work
Maintenance diy, etc	unpaid_work
Consuming services	leisure
church,temple,synagogue,prayer	leisure
walking, Jogging	leisure
travel: cycle	other
Travel by car	other
Travel by bus,tram	other
Travel by train,tube	other
Travel other	other
Paid work including at home	work
Formal education	other
Recreational courses	leisure
Voluntary work for organisation	unpaid_work
Caring for own child	unpaid_work
Caring for other children	unpaid_work
Help,caring for cores adult	unpaid_work

Help,caring for noncoresidents	unpaid_work
Work,study break	rest
Shopping,bank etc incl internet	other
Watching tv,video,dvd,music	leisure
Reading including e-books	leisure
Playing sports, exercise	leisure
Going out to eat, drink	leisure
Walking,dog walking	leisure
Playing computer gamesm	leisure
Ttime with friends,family	leisure
Telephone,text,email,letters	other
Cinema,theatre,sport etc	leisure
Hobbies	leisure
write-in other	other
138	other

Appendix C

Available at: https://github.com/jamesalster/Condemned-to-Leisure---Time-Use-during-the-first-UK-Lockdown-in-Spring-Summer-2020/blob/main/Appendix_C.odt

Code Appendix

Available at: https://github.com/jamesalster/Condemned-to-Leisure---Time-Use-during-the-first-UK-Lockdown-in-Spring-Summer-2020