Can British homeworkers have more stable work schedules? A time-use approach to measure work schedule instability

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## 1. Introduction

A growing body of literature recognises that ‘work schedule instability’ can lead to worse well-being status and a series of mental issues, including irregular health practises, mental distress, poor sleep quality, and unhappiness (Schneider and Harknett 2019; Ananat and Gassman-Pines 2020). Although there is a rich research tradition investigating the consequences of work schedule instability for worker health and well-being (Carrillo et al. 2017a; Harknett, Schneider, and Wolfe 2020; Luhr, Schneider, and Harknett 2022), far too little attention has been paid to the predictors of work schedule instability. In addition, the definitions and measurements of work schedule instability in current literature are almost all based on respondents’ irregular work arrangments controlled by employers (i.e., cancelled shifts or any schedule change experience) (Carrillo et al. 2017a; Harknett, Schneider, and Wolfe 2020) or working time patterns based on long-term memories (i.e., week-to-week hours variation in the past month) (Schneider and Harknett 2019) but not 24-hour daily time use data. The studies that use these ‘work-domain-oriented’ measurements tend to assume ‘work schedule instability’ are mainly caused by factors in the work domain but ignore the fact that workers also can control their work schedule to facilitate private/family demands, thereby increasing their work schedule instability (Chung and Booker 2022; Cornwell 2013). In particular, during the last decades, flexible working arrangements have become common rights in the UK labour market, which allow workers to decide when and where to work flexibly (Lu and Zhuang 2023a). Such changes led to numerous debates and studies aimed especially at predicting the impacts of working from home on time use patterns and time quality indexes related to work-life balance (Offer and Schneider 2011; Craig and Brown 2016). Therefore, it is necessary to find out an objective measure of work schedule instability based on workers’ accurate time use data.

      In this study, we expect that working from home can shape workers’ work schedule instability by offering more work autonomy and flexibility, while such associations still subject to ongoing debates due to the lack of empirical evidence. On the one hand, according to the resource (drain) perspective in the work‐family spillover theory (Greenhaus and Beutell 1985; Frone, Russell, and Cooper 1992), some scholars predict that workers tend to have more time and energy to manage their work schedule when working from home since they might have more work autonomy and flexibility to address work-family conflicts (Lu and Zhuang 2023b; Li and Wang 2022). On the other hand, some sociologists of work are worrying about the potential adverse effects of working from home and emphasise the potential role-blurring effects (Yucel and Chung 2021; Wheatley 2012). This is because workers might increase work schedule instability when working from home due to the blurring of the temporal and spatial boundaries between their work commitments and private life (Zerubavel 1979; Clark 2000). Overall, there are conflicting theoretical predictions about the associations between working from home and work schedule instability. Owing to the limitation of time use data and methods used, no direct dialogue is available. Therefore, the study’s first objective is to explore how working from home shape workers’ work schedule instability by using 24-hour time use data to measure work schedule instability.

       Moreover, given that workers’ experience in the labour market and time use patterns are highly gendered and class-differentiated, we expect that the associations between working from home and work schedule instability might vary across gender, occupational class and the combination of the two. For men, workers in the higher (i.e., professional and managerial classes) groups and the lower (i.e., routine and manual classes) groups share different bargaining power and job demands and security, making them suffer different risks in terms of work schedule instability (Dumont, Rayp, and Willemé 2012; Warren 2015; Bianchi et al. 2014). For example, the higher occupational groups might exchange the right to work at home with their high bargaining power (Dumont, Rayp, and Willemé 2012), while the lower groups might passively work at home since they do not have other choices (Bathini and Kandathil 2017). As for women, other than class disparities in the labour market, female workers in different occupational classes suffer from different stress-related exposures and different degrees of worse time quality (i.e., time fragmentation and contaminated free time) in their households (Carrillo et al. 2017b; Craig and Brown 2016), making them at different risk when working from home and dealing with work schedule instability. For instance, women in the lower occupational groups might share more household responsibilities and have fewer resources (i.e., money, time and energy) to manage work schedules (Hu and Yucel 2017; Syrda 2022).

       By achieving both objectives, this study tends to make two important contributions to the literature. First, we empirically extend the previous research by developing an objective measure of work schedule instability by using workers’ 24-hour time use data. Specifically, in the UK time use survey 2020-2021, respondents were asked to record every single working episode (10 minutes/1 episode) within 24 hours. Thus, we are able to identify ‘hamming distance’ to measure similarities between sequences (Lesnard 2010). (Here we need more introduction about hamming distance). See Table [X] for more details about the measurement of hamming distance. Second, the study provides novel insights into the debate about whether and how working from home shapes workers’ work schedule instability across gender and occupational class.

## 2. Literature review

## 3. Analysis

The sample of this study is drawn from the Centre for Time Use Research (CTUR) UK Time Use Survey across the COVID-19 pandemic. The dataset is a population-representative (quota sample) time-use diary data collected by the Centre for Time Use Research through an online Click and Drag Diary Instrument (CaDDI). Representative quotas were established for the gender, age group, region, and social class distribution of the population. As part of the survey, respondents were given online time-use diaries, and were asked to record what they were doing, how they were doing it, and their feelings towards their activities during 144 10-minute episodes across the day (Sullivan et al. 2021). In addition to the diaries, the dataset contains information about standard socio-demographic variables and mental health. Respondents completed the online time-use diaries for between 1 and 3 days, yielding diary data for around 5800 diary days across 2020-2021. The sample first excluded those who were not in paid employment. Then, we selected those who reported at least two work diary days as the target sample (X%). After excluding the samples with missing data (around X%) or extreme values such as 0 or 24 working hours per day (around X%), The final analytic sample came to include X adult workers who have at least two 24-hour working day diaries. More details about the sample can be seen in Table X.

**Data cleaning (using stata)**

**Note:** I can change it to R code later

//6896 observations in total  
use "uk\_6\_wave\_caddi.dta",replace  
//keep wave2 - 6  
drop if survey==1  
//(1,011 observations deleted)  
//left 5885 observations  
save "uk\_5\_wave\_caddi.dta",replace  
   
//keep people who are in working status (Employment situation now)  
keep if emplnow<5  
keep if emplnow>0  
keep if econstat==3  
//3051 left  
  
//generate a new variable: working from home(2) or not(1)  
g wfh=emplnow  
recode wfh 1/2=1 3/4=2  
//1896 changes made to wfh  
  
//keep work days, drop weekend data  
drop if dday==6  
//509 observations deleted  
drop if dday==7  
//2059 left  
save "5wave-cleaned.dta" ,replace  
  
//g work  
foreach var of varlist pri1-pri144 {  
egen w\_`var' = anymatch(`var'),v(117)  
}  
  
egen paidwork=rowtotal(w\_pri\*)  
  
//housework  
foreach var of varlist pri1-pri144 {  
egen h\_`var' = anymatch(`var'),v(105,106,107,108,121,122,123,124,126)  
}  
  
//Free time-leisure actrivities  
foreach var of varlist pri1-pri144 {  
egen f\_`var' = anymatch(`var'),v(102,111,112,113,114,115,116,125,127,128,129,130,131,132,133,135,136)  
}  
  
//Personal care  
foreach var of varlist pri1-pri144 {  
egen p\_`var' = anymatch(`var'),v(101,103,104,109,110)  
}  
  
//recode class into two categories  
g class=dclasuk  
drop if class>3   
//34 observations deleted  
recode class 1=1 2=2 3=2  
  
//Monthly personal income from paid work  
g income=labin2  
replace income=. if income<0  
//94 to missing  
  
//Annual household income from any source  
g hincome=hhincom2  
replace hincome=. if hhincom2<0  
//69 to missing  
recode hincome 1=1 2/3=2 4/5=3 6/7=4 8/9=5 10=6 11=7  
  
//presense of children in household  
g pchild=nkids  
recode pchild 0=0 1/5=1  
  
//how you were working before the 'lockdown'?  
g wfh\_b=empbfore  
recode wfh\_b 1/2=1 3/4=2 5/9=3 98=3  
  
//Whether diary day was typical  
keep if typical==1  
//296 observations deleted  
//1763 left  
save "3days\_cleaned0928.dta" ,replace  
  
egen pidp = group( mainid diaryord)  
order pidp  
sort pidp  
save "3days\_cleaned0928.dta" ,replace

## Loading required package: pacman

if (!require("pacman")){  
 install.packages("pacman")  
 library(pacman)  
}

Loading required package: pacman

## load and install packages

pacman::p\_load(TraMineR, TraMineRextras, cluster, RColorBrewer, devtools, haven,   
 tidyverse, reshape2, WeightedCluster, nnet, data.table, Statamarkdown, AER)

## Load .dta (Stata) Dataset

# setwd("E:/OneDrive/SciencesPo/data")  
## LL: you should create a R project using this directory instead of setting manually your working directory  
## it makes your code stronger and independent of personal configurations  
x3 <- read\_dta("3days\_cleaned0928.dta")  
## I would also suggest not to use capital letters for R objects as it makes the code a little bit more difficult to write  
## and if you use only lower cases as a rule, it makes R code safer from case errors

## Read data UKTUS 3days cleaned

## Keep those who have at least 2 diary days (new subset: d2)

At this stage, we drop (1763-1164=599) cases

x3 <- x3 %>%  
 group\_by(mainid) %>%  
 mutate(ndays = n())  
d2 <- x3 %>%  
 filter(ndays >= 2)  
head(d2$mainid)

[1] 20037 20037 20038 20038 20048 20048

## Calculate the manhattan distance

setDT(d2)  
  
distances\_df <- d2[, .(distance = dist(.SD, method = "manhattan")), by = mainid, .SDcols = w\_pri1:w\_pri144]  
print(distances\_df)

mainid distance  
 1: 20037 0  
 2: 20038 29  
 3: 20048 9  
 4: 20050 11  
 5: 20057 0  
 ---   
620: 60479 11  
621: 60483 3  
622: 60495 48  
623: 60510 41  
624: 60518 53

mean\_distances <- distances\_df[, .(mean\_distance = mean(distance)), by = mainid]  
  
d2 <- d2 %>%   
 left\_join(mean\_distances, by = "mainid")  
  
summary(d2$mean\_distance)

Min. 1st Qu. Median Mean 3rd Qu. Max.   
 0.00 1.00 8.00 15.21 22.00 144.00

## Slice the sample, keep only one observation for each respondent

At this stage, we drop (599-568=31) cases

# d2 <- read\_dta("d2.dta")  
# Am I right to assume that you exported the above d2 file to stata? It does not appear in the syntax file as it should be : this document must be autonomous  
  
d3 <- d2 %>%  
 group\_by(mainid) %>%  
 slice\_sample(n = 1)

## Drop cases who were not in paid employment

At this stage, we drop (568-567=1) cases

d3 <- d3[d3$dclasuk <4, ]

## Weight

frequency\_sex <- table(d3$sex)  
percentage\_sex <- prop.table(frequency\_sex) \* 100  
print(frequency\_sex)

1 2   
344 224

print(percentage\_sex)

1 2   
60.56338 39.43662

##sex (1)male (2)female

d3 <- d3 %>%  
 mutate(weight = case\_when(  
 sex == 1 ~ 1.264,   
 sex == 2 ~ 0.756,   
 ))

frequency\_class <- table(d3$dclasuk)  
percentage\_class <- prop.table(frequency\_class) \* 100  
print(frequency\_class)

1 2 3   
340 110 118

print(percentage\_class)

1 2 3   
59.85915 19.36620 20.77465

##dclasuk: 1(high) 2(mid) 3(low)

d3 <- d3 %>%  
 mutate(class\_weight = case\_when(  
 dclasuk == 1 ~ 1.259,   
 dclasuk == 2 ~ 1.142,   
 dclasuk == 3 ~ 0.585,   
 ),  
 combined\_weight = weight \* class\_weight)

frequency\_age <- table(d3$agegroup)  
percentage\_age <- prop.table(frequency\_age) \* 100  
print(frequency\_age)

1 2 3   
162 315 91

print(percentage\_age)

1 2 3   
28.52113 55.45775 16.02113

##agegroup: 1(min/34) 2(35/54) 3(55/max)

d3 <- d3 %>%  
 mutate(age\_weight = case\_when(  
 agegroup == 1 ~ 1.037,   
 agegroup == 2 ~ 0.837,   
 agegroup == 3 ~ 1.495,   
 ),  
 final\_weight = combined\_weight \* age\_weight)

## Predict schedule instability

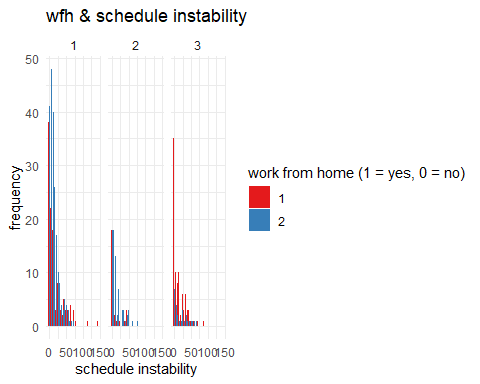
## Discriptive statistics

d3\_summary <- d3 %>%  
 group\_by(dclasuk, wfh) %>%  
 summarise(  
 mean\_satisfaction = mean(mean\_distance, na.rm = TRUE),  
 median\_satisfaction = median(mean\_distance, na.rm = TRUE),  
 sd\_satisfaction = sd(mean\_distance, na.rm = TRUE),  
 n = n()  
 )

`summarise()` has grouped output by 'dclasuk'. You can override using the  
`.groups` argument.

# 按阶级分类，创建直方图  
ggplot(d3, aes(x = mean\_distance, fill = factor(wfh))) +  
 geom\_histogram(bins = 30, position = "dodge") +  
 facet\_wrap(~ factor(dclasuk)) +  
 labs(title = "wfh & schedule instability",  
 x = "schedule instability",  
 y = "frequency",  
 fill = "work from home (1 = yes, 0 = no)") +  
 theme\_minimal() +  
 scale\_fill\_brewer(palette = "Set1")

Don't know how to automatically pick scale for object of type <dist>.  
Defaulting to continuous.



## Regression OLS

frequency\_wfh <- table(d3$wfh)  
percentage\_wfh <- prop.table(frequency\_wfh) \* 100  
print(frequency\_wfh)

1 2   
257 311

print(percentage\_wfh)

1 2   
45.24648 54.75352

##agegroup: 1(min/34) 2(35/54) 3(55/max)

model1 <- lm(mean\_distance ~ factor(wfh)+ factor(dclasuk) + factor(sex)+factor(pchild)+factor(agegroup)  
 , data=d3, weight= final\_weight)  
summary(model1)

## Moderating role of class

model2 <- lm(mean\_distance ~ factor(wfh)\*factor(dclasuk) + factor(sex)+factor(pchild)+age  
 , data=d3, weight=final\_weight)  
summary(model2)

## Plot the interaction

Error in contrib.url(repos, "source"): trying to use CRAN without setting a mirror

Warning: package 'ggplot2' is in use and will not be installed

Attaching package: 'emmeans'

The following object is masked from 'package:devtools':  
  
 test

Error in eval(expr, envir, enclos): object 'model2' not found

Error in eval(expr, envir, enclos): object 'emm\_interaction' not found

## Predict interaction terms using the model results

emm\_df <- as.data.frame(emm\_summary)

Error in eval(expr, envir, enclos): object 'emm\_summary' not found

ggplot(emm\_df, aes(x = factor(wfh), y = emmean, group = factor(dclasuk), color = factor(dclasuk))) +  
 geom\_line() +  
 geom\_point() +  
 labs(x = "Work From Home (WFH) Factor", y = "Estimated Marginal Mean", color = "Dclasuk Factor") +  
 theme\_minimal() +  
 ggtitle("Interaction Effects in Model 2")

Error in eval(expr, envir, enclos): object 'emm\_df' not found

## Repeat by using Tobit

model\_tobit1 <- tobit(mean\_distance ~ factor(wfh) + factor(dclasuk) + factor(sex)+factor(pchild)+age,  
 data = d3, weights = final\_weight, left=0)  
  
summary(model\_tobit1)

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