The Changing Nature of Work: What can we learn from Time Use Diaries?

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Abstract

We use new time diary data from the UK Office for National Statistics (April 2020–March 2025) to examine the persistence of remote work and its relationship to time use, well-being, and self-perceived productivity. Remote workers spend over an hour less commuting per day than on-site workers. They allocate this time toward sleep, unpaid work and caregiving, and health-related leisure, and exhibit greater temporal flexibility by shifting work away from early mornings and mid-day hours toward the late afternoon. Despite these adjustments, remote workers report lower instantaneous enjoyment and self-assessed productivity whilst working. Our findings suggest that the sustained use of remote work is driven less by perceived gains in productivity or well-being in work and more by the avoidance of commuting and increased flexibility in non-work activities. These results have implications for the design of hybrid work arrangements and contribute to broader discussions on time allocation, labour supply, and commuting behaviour.

Keywords: time use diaries, working from home, instantaneous enjoyment, self-perceived productivity.

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1. Introduction

The sharp rise of remote work since 2019 has fundamentally reshaped labour markets and daily life. Initially emerging as a temporary response to global health restrictions, imposed with the onset of the COVID-19 pandemic, remote work increasingly looks to be a permanent shift in the way work is structured (Aksoy et al, 2022; Hansen et al, 2023; Buckman et al, 2025).

This transformation raises important considerations for employers and policymakers seeking to promote business and macroeconomic competitiveness as these new working arrangements have implications for productivity, economic efficiency, workforce characteristics and quality (Lee, 2023). The shift towards remote working has also significant consequences for workers, potentially affecting career options, commuting behaviours, work-life balance and wellbeing. Remote work may also promote or hinder gender equality in the labour market, by reshaping the distribution of paid and unpaid work between men and women. Understanding why workers continue to choose remote work, even when it may involve trade-offs such as reduced wages (Barrero et al, 2021; Nagler et al, 2022; Cullen at al., 2025) and reduced wage growth (Barrero et al, 2022; De Fraja et al, 2025), remains crucial for understanding the motivations that sustain these arrangements.

From a revealed-preference perspective, the persistent choice of remote work implies that, on balance, workers derive higher overall utility from this arrangement than from on-site work (Gibbs et al., 2024). However, observed choices alone do not identify the underlying sources of this utility, nor how different dimensions of well-being are affected. Remote work may involve trade-offs between work-related enjoyment or productivity, commuting costs, temporal flexibility, and the organisation of paid and unpaid activities over the day. Disentangling these components is therefore essential for understanding what workers value in remote work and how it affects their experienced well-being.

In this paper, we examine longer term trends and differences between remote and office workers in time allocation and wellbeing. Our analysis focuses on how different work arrangements shape daily life patterns, including commuting behaviours, work-life balance, and the distribution of paid and unpaid activities. The ability to work from home has previously been associated with greater flexibility, reduced commuting time, and potential cost savings (Aksoy et al, 2023). Compared to previous studies, the examination of newly collected time-use diaries allows for a more systematic investigation of the post-pandemic "new normal" in the UK.

Existing studies have shed light on broad patterns of remote work and employees' preferences using specially designed employee surveys (Barrero et al., 2022, 2023) and employer surveys (Jones et al., 2024). Closest to our approach, some studies have explored the relationship between remote work and the time allocation of workers and households for US and UK employees (Restrepo and Zeballos, 2022; Pabilonia and Vernon, 2022; Giménez-Nadal et al, 2024; Cowan, 2024). These studies largely consider the period up to two years after the COVID-19 pandemic. The sustained implications of remote work after the pandemic remain an open question.

The incidence of remote working in the UK is amongst the highest in the world (Zarate et al., 2024). We develop and use new experimental time use data for the UK to consider the relationship between remote work, wellbeing and self-perceived productivity, updating and extending existing evidence. One of the key advantages of time-use data in this context is that it allows us to collect data on remote work independently of worker preferences. Thus, we avoid the potential biases that arise from the use of directed questions on remote work, which underpin much of the available evidence. Compared to existing studies, our data offer a more comprehensive view of how remote and hybrid work shapes daily life and helps reveal the underlying preferences that have sustained them in the post-pandemic labour market.

We examine three key research questions. First, we ask whether time use diaries, collected consistently over time, can be used to provide new information about remote work trends in the UK.[1] There are only few repeated surveys that allow researchers and policy makers to monitor changes in work patterns over time. Recurrent time use surveys can add to this by showing the proportion of respondents in employment who report working partly or only from home during weekdays and the number of hours in their workday compared to that of office workers. Second, we examine whether individuals working from home spend less time on paid work and commuting, and more time on activities they value more. We also analyse whether remote workers engage more in multitasking while at work, allocate their working hours differently across the day and report higher enjoyment during work and non-work activities compared to those working on-site. Third, we assess whether remote workers perceive themselves to be more productive than their counterparts in traditional office settings. We also investigate whether the association between remote work and time use, enjoyment and self-perceived productivity differs by gender.

[1] We will refer to remote work to include all forms of working from home (fully remote, hybrid work).

To address these questions, we analyse and develop a new survey of time use collected by the UK's Office for National Statistics (ONS) between April 2020 and March 2025, offering a comprehensive view of evolving work behaviours. The ONS online time use survey (OTUS) allows us to compare work patterns across different time periods, benchmarking on earlier surveys from 2014/2015. We examine how individuals allocate time to various activities when working remotely versus in the workplace, and their instantaneous enjoyment associated with these activities. We extend the two most recent waves of the OTUS data to elicit information on workers' self-perceived productivity during detailed work episodes and under different working arrangements. By leveraging these extensive datasets, we provide empirical insights into the factors that contribute to workers' decisions to continue working remotely and draw attention to potential implications for policymakers and employers.

Our findings reveal several important trends. First, remote work has remained a stable feature of the labour market beyond the immediate effects of the pandemic. Many workers continue to report time in remote working four years after the relaxation of social restrictions. This result contributes to the literature on measuring working from home (Barrero et al, 2024; Buckman et al, 2025; Kmetz et al, 2025) showing that time use data can be used to establish trends in work patterns while also providing detailed information on other aspects of work and everyday life.

Second, we find that remote workers generally spend over an hour less in transport. They reallocate this time toward sleep, unpaid work and caregiving, and health-related leisure. They also exhibit greater temporal flexibility by shifting work away from early mornings and mid-day hours toward the late afternoon. Furthermore, home working is associated with more multitasking: remote workers report more time spent in leisure as a secondary activity when the main activity is working. Despite these differences, we find that working from home is not associated with higher instantaneous enjoyment than working away from home. These results are robust to controls for individual fixed effects. Our new findings for the UK contribute to the literature on time use and wellbeing of remote workers by supporting the early findings that remote work inherently leads to more multitasking, leisure or unpaid work (Adams et al, 2023; Aksoy et al, 2023b; Cowan, 2024; Gimenez Nadal et al, 2024), while challenging the evidence that it enhances wellbeing (Denzer and Grunau, 2024).

Third, our results show that both men and women increase their time in unpaid work when working from home. This pattern implies that the gender gap in unpaid work and care remains largely unchanged. Even so, the fact that a substantial share of men takes on more unpaid work and care when working remotely may contribute to gradual shifts in gender norms around housework and caregiving responsibilities (Farré et al, 2023).

Fourth, workers' perceived productivity is marginally lower with remote work, suggesting that the choice to work from home may not be primarily driven by efficiency gains in work, as is sometimes suggested. These findings are robust to the inclusion of a large set of demographic characteristics, as well as detailed occupation and income bands.

Taken together, these findings form a coherent picture when viewed through the lens of revealed preferences. Workers persistently choose remote work despite evidence that it carries wage penalties, yet it does not make work itself more enjoyable or more productive: our results show the opposite. The utility of remote work appears to derive from what surrounds work rather than from the work experience itself, namely from the elimination of commuting, from the flexibility to reorganise working hours, and from the greater time available for sleep, caregiving, and health-related leisure. Our results thus bring new evidence to the literature on workers' incentives for remote work (Bloom et al, 2023; Ramani et al, 2023; Cullen et al., 2024).

Together, these insights contribute to the ongoing literature about the future of work by offering an updated perspective on how workers allocate time and what may motivate their choices. The study highlights the need for employers to carefully evaluate the benefits and challenges of remote work policies, particularly when designing hybrid work models. For policymakers, our findings emphasise the importance of addressing commuting inefficiencies and work-related expenses, which appear to be important drivers in the decision to work from home.

The rest of the paper is organised as follows. Section 2 sets out the UK context. Section 3 presents the data. Our analytical approach is illustrated in Section 4 and main results discussed in Section 5. Section 6 concludes.

2. UK Context

As it did in many countries, the COVID-19 pandemic triggered an unprecedented disruption to the UK labour market, reshaping working patterns through strict public health measures and government intervention. The UK experienced three national 'strict' lockdowns - March to July 2020, November 2020, and January to June 2021 - that forced many workers to operate remotely while the Coronavirus Job Retention Scheme (furlough) sustained employment for those unable to work from home. These measures, while essential in mitigating economic collapse and reducing contagion, introduced profound shifts in work organisation, the effects of which continue to shape the post-pandemic landscape of work arrangements.

The most significant shift was the widespread adoption of remote working. Figure 1 shows the proportion of respondents in work who reported working mainly or partly from home in the Annual Population Survey (APS), broken down by gender, highest qualification, health status, and age. The proportion of all workers working mainly or partly from home rose from 14% in 2019 to 30% in 2022 and remained stable at that level thereafter.[2] This reported increase is compared to the predicted proportion based on probit estimates for the period 2012–2019. Notably, this shift led to a gender convergence in remote work, with women, who were less likely to work from home before 2020, experiencing a sharper rise compared to men (top left panel). The shift to remote work was primarily driven by graduate workers (top right panel) rather than older workers (bottom right panel) or those with pre-existing health conditions (bottom left panel). The greater likelihood of transitioning to remote work for workers with a college degree is observed by Barrero et al. (2023) also for the US and for other countries, reflecting occupational differences between knowledge-based roles and jobs requiring physical presence.

Figures A1 and A2 in Appendix A show that the increase in remote work was largely concentrated among workers in professional, managerial, associate professional, and administrative roles (Standard Occupational Classification – SOC – codes 1 to 5). It was also more prevalent in London and South-East England, where these jobs are more likely to be located. Transport data from major cities further corroborate the shift to remote work, with a decline in weekday commuters - particularly train, underground, and, to a lesser extent, bus passengers - between 2019 and 2023 (Figures A4 and A5, Appendix A). Moreover, comparing observed patterns in the prevalence of working from home with pre-pandemic predictions confirms that this shift was a structural break rather than a mere acceleration of existing trends.[3]

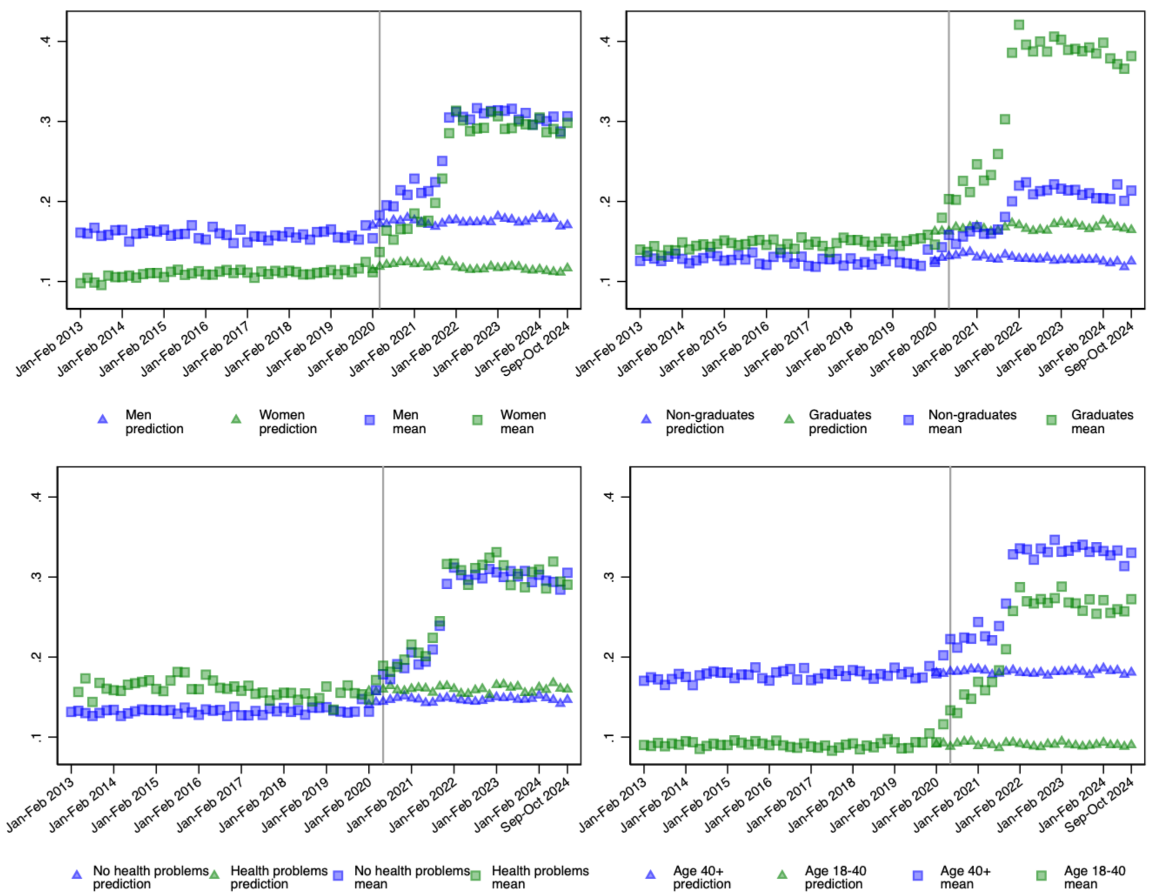
While conventional survey data covering labour market topics provide valuable insights into shifting work patterns, a deeper understanding requires examining how individuals allocated their time during and after the pandemic. Surveys capture broad trends in remote work adoption and working hours but fail to reveal the nuances of how work was structured within daily routines or the extent to which professional, domestic, and leisure activities overlapped or changed in their time allocation and their enjoyment - factors that could have implications for productivity, worker well-being and their

[2] As reported in Aksoy et al (2022), the UK was one of the countries with the highest number of paid, planned and desired full days working from home at the end of 2021 and beginning of 2022.

[3] Figure A3 in Appendix A shows the proportion of APS respondents who report working mainly from their own home. The gaps in this proportion across socio-demographic groups are small or non-existent before 2019. After the COVID-19 pandemic this proportion shifted from .5 to .20, mostly driven by graduate workers.

preferences. To address this gap, we turn to time-use data, which offer granular insights into how work is integrated with other activities. Continuous time-use diaries are widely regarded as the best tools for tracking behavioural changes, as they minimize recall bias and are less influenced by social desirability bias compared to survey questions (Gershuny et al., 2019; Sullivan et al., 2021). These data allow us to assess not only remote workers' allocation of their time between total working hours and other activities but also shifts in multitasking. New time use data are also a tool to capture the enjoyment of workers for different activities and their self-reported productivity for each spell of work.

Figure 1: Proportion working mainly or partly from home and predictions – by gender, college degree, health status and age



Notes. The figure shows the bi-monthly proportion (square markers) of respondents working mainly or partly from home (WFH) and the prediction out of sample (triangle markers) for the period January 2020 – September/October 2024 based on APS data. The binary variable WFH is one when respondents report working from their own home, from the same grounds or building or different places with home as a base. Predicted proportion of WFH for the years 2020 - 2024 was obtained by first estimating, separately by sub-sample, a probit for the reported working from home on age, highest qualification, economic activity, occupations, region of residence, marital or cohabiting status, a time trend, a squared and cubic time trend and month dummies for the years 2012-2019 and then averaging the out-of sample individual predictions by sub-sample and time. Predictions and means are obtained using the individual weights provided in the APS.

3. Time Use Data

We use new nationally representative data from the United Kingdom, collected with time use diary surveys during and after the COVID-19 pandemic: the On-line Time Use Survey (OTUS) data, developed by the ONS. OTUS was designed to enhance the measurement of unpaid household production and caregiving, facilitating a more comprehensive assessment of their economic significance, while also providing a deeper understanding of time use in relation to well-being and quality of life. Respondents are UK adults aged 18 and over, from the NatCen Opinion Panel. Although some respondents may be interviewed in more than one wave, the survey is designed as a repeated cross-section. Data collection took place across nine waves between 2020 and 2025. The first three waves were conducted in March–April 2020 during the first COVID-19 lockdown, September–October 2020 as most restrictions were lifted, and March 2021 amid the vaccine rollout. From wave 4 onward, time-use data collection followed a more regular pattern, with subsequent waves in March 2022, November 2022, March 2023, September–October 2023 and March 2024. The most recent wave was collected in March 2025. Participants completed two diary days—one on a weekday and one on a weekend. Activities were recorded using a predefined list of 116 activity codes (see Appendix Table C8).

Primary activities were reported in 10-minute intervals, while up to five secondary activities were captured in five-minute intervals. Co-presence and location for each activity are not recorded, however respondents are asked to select different activity codes for work from home and work from the workplace. The WFH indicator is thus derived from respondents's activity-code choices, not from a separate location field. A follow up question appearing in a pop-up window after each activity collects information about instantaneous enjoyment on a seven-point scale, allowing collection over a 24-hours period. We use this measure as a proxy for wellbeing. A picture of the online instrument used by the ONS to collect time use diaries is provided in figure B1, Appendix B. To enable us to better understand the relationship between remote work and productivity, we introduced from March 2024 a new, and experimental, follow-up question on self-perceived productivity that was asked every time respondents selected a spell of paid work. The question asked was "During this time, roughly how productive were you?" and the possible choices were "1 = 100% productive; 2 = 90-99% productive; 3 = 80-89%

productive; 4 = 70-79% productive; 5 = Less than 70% productive" as shown in Figure B2, Appendix B.[4]

The final sample of OTUS data used in this analysis includes 7,555 weekday diaries collected between April 2020 and March 2025. We restrict the sample to individuals (employees) reporting at least four hours of paid work per day in order to focus on a more homogeneous group of workers and to exclude marginal or casual employment with very limited daily working time. Appendix C (Table C1) presents the main demographic and socio-economic characteristics of the 4386 respondents in the sample November 2022 – March 2025 that we use for most of our regression models. A comparison across waves indicates that the respondent pool remains balanced; however, women and individuals with a college degree are overrepresented compared to national averages. This is less problematic for the purposes of our analysis, as graduates are also more likely to work from home and therefore constitute a core component of the population of interest. To account for these differences, we apply sample weights provided by the ONS. Table C3 compares main weighted summary statistics for the APS, the main household survey in the UK, and OTUS data showing that the weighted samples are very similar.

We use OTUS data to construct measures of daily time spent in paid work and other activities by location (workplace or home).[5] These data allow us to examine how trends in working from home evolved during the pandemic and in the post-pandemic "new normal". We then focus primarily on the post-pandemic period to study the association between working from home and daily time allocation across activities, enjoyment of work, and engagement in secondary activities while working. Additionally, for March 2024 and March 2025, we are able to consider, alongside the enjoyment of work episodes, contemporaneous self-perceived productivity and its relationship with remote work. Enjoyment and productivity are recorded independently of the location of activities. Importantly, given that each respondent provides a single diary day, our measures of time use, enjoyment and self-perceived productivity capture time use on days in which individuals work from home for at least four hours in a weekday, rather than the typical time allocation of workers with different long-run remote working arrangements. Table C2 in Appendix C provides descriptive statistics for time-use measures from OTUS diaries of employed respondents. Lastly, Appendix C (Figures C1 and C2) presents the

[4] This question was developed by the Cabinet Office to study the productivity and effectiveness in the Civil Service. The wording of the question was informed by cognitive testing that suggested individuals were confident they were able to assess their own productivity, but not their productivity in comparison to others; individuals mostly associate productivity with delivery or completion of work (e.g. delivering on objectives, getting work done) and use of time (e.g. meeting deadlines, hitting milestones, efficiency). Some also associate productivity with a feeling of making a difference.

[5] The full set of categories of activities considered in the paper is the following: sleeping, personal care, travelling, unpaid housework, unpaid care, watching TV, leisure, fitness/wellbeing related leisure and internet/social media. Detailed activities by activity category are presented in table C7 (Appendix C).

distributions of self-reported productivity and work enjoyment for sample in the last two waves of OTUS data.

4. Analytical approach

We begin with a descriptive comparison of the proportion of weekday diaries reporting remote work in the OTUS data over time with the corresponding proportion in the UK Time Use Survey 2014/15, after selecting a comparable sample of workers.[6] This comparison enables us to describe and quantify the shift toward working from home during and after the pandemic based on time use diary data.

To study the changing nature of work arising from the shift to remote work, we first compare time use across different activities between diary days in which work is performed at home and diary days in which work is performed away from home and examine whether these differences vary by gender. Given that each respondent contributes only one diary day, this comparison should be interpreted as contrasting time allocation on working from home days versus non-working from home days, rather than as differences between workers with distinct long-run remote working arrangements. Second, we investigate how working from home on the diary day is associated with patterns of multitasking, instantaneous enjoyment, and self-reported productivity. To understand the association between time use and remote working we estimate the following equation:

$$Time_{iq}^{a} = \alpha + \beta WFH_i + \delta Female_i + \gamma WFH_i * Female_i + X_i\zeta + \Sigma\xi_q D_q + \varepsilon_{iq}^{a} \qquad (1)$$

Where the dependent variable $Time_{iq}^{a}$ represents the reported measures of total diary time for individual i in activity a (*sleeping, personal care, travel, unpaid work, unpaid care, watching television, leisure, wellbeing and fitness, social media/browsing the internet, total time in paid work*) in wave q; WFH is a binary indicator taking value 1 if the respondent works from home at least four hours in the diary day, and 0 otherwise; *Female* is a dummy variable for whether the respondent is a woman; X is a comprehensive set of individual characteristics, 2-digits SOC code occupation dummies and region dummies; D_q is a set of wave dummies and, finally, ε_{iq}^{a} is an idiosyncratic error term.[7] Our coefficients of interest are β for men and $\beta + \gamma$ for women as they capture the difference in time use between remote workers and office workers. A similar approach is then used to estimate the difference

[6] The UK Time Use Survey 2014–15 (UKTUS) is a nationally representative study that collects detailed information on how people allocate their time across daily activities. It was conducted between April 2014 and December 2015.
[7] All regressions include the following set of individual characteristics: education levels, age, relationship status, number of children, ethnicity, house tenure, indicators for income bands, indicator for whether the respondent has a health condition, total workhours in the week.

in multitasking between office and remote workers: in this case $Time_{iq}^{a}$ is time spent in secondary activities while the main reported activity is paid work.

We use OTUS data to investigate instantaneous enjoyment across different groups of activities (treating paid work at the workplace and paid work at home as distinct activities) by estimating the following equation separately for men and women (g=Men, Women), controlling for individual fixed effects:

$$\begin{aligned} Enj_{ijq}^{g} = \beta_0 + \beta_1^g Travel_{ij} + \beta_2^g Unpaid\ Work_{ij} + \beta_3^g Unpaid\ care_{ij} \\ + \beta_4^g Work\ from\ office_{ij} + \beta_5^g Work\ from\ home_{ij} \\ + \beta_6^g Watching\ Television_{ij} + \beta_7^g Leisure_{ij} + \beta_8^g Fitness_{ij} \\ + \theta_i + \gamma T_{ij} + \varepsilon_{ijq}^{g} \qquad (2) \end{aligned}$$

The dependent variable Enj_{ijq} is the instantaneous enjoyment reported by individual *i* for episode *j* in wave q; *personal care, travel, unpaid work, unpaid care, watching television, leisure, wellbeing and fitness, paid work from home* and *paid work from the office* are binary indicators for the main types of activities, where the baseline is sleeping and personal care, activities that are inevitable and therefore reported by all respondents in the sample; T_{ij} is the total time of the episode and θ_i are individual fixed effects.[8] Since each respondent contributes a single diary day comprising multiple activity episodes, θi is identified across episodes reported on the same day, controlling for each individual's overall enjoyment rating tendency on that diary day, including any effect of mood or general disposition. The comparison between the enjoyment of working from home and working from the office is therefore made within the same person on the same day. Our coefficients of interest are β_k^g (where $k = 1,..8$), as they capture differences in enjoyment across activities relative to sleeping and personal care, net of observed controls and unobserved individual heterogeneity. In particular, the comparison between β_4^g and β_{k5}^g quantifies the conditional difference in enjoyment between working from home and working from the office, holding constant individual-specific factors and episode duration. The aim of this analysis is therefore to assess whether, after accounting for such heterogeneity, respondents exhibit a systematic preference for working from home relative to working from the workplace.

[8] The full list of OTUS activity is reported in Table C7, Appendix C.

Finally, we focus on work episodes reported in the last two waves of the OTUS data (March 2024 and March 2025) and estimate the association between working from home and the self-perceived productivity (as well as enjoyment for a comparison) by estimating the following equation:

$$Prod_{ijq} = \alpha + \beta WFH_i + \delta Female_i + \gamma WFH_i * Female_i +$$

$$+X_i \zeta + \xi D_{march2025} + \varepsilon_{ijq} \quad (3)$$

The dependent variable $Prod_{ij}$ is the measure of self-perceived productivity for individual i collected by OTUS only for episodes j of work and is defined on a five-point scale where 1 is the highest productivity and 5 is the lowest. For the analysis we revert this scale such that a positive estimate for γ_2 and $\gamma_2 + \gamma_3$ would imply that respondents perceive a higher productivity when working from home. We also transform this five-points scale into dichotomous indicators according to different cut-offs and use probit models to estimate the association between working from home and self-perceived productivity as marginal effects.[9]

However, because individuals may select into working from home on particular days depending on the nature of tasks or their expected productivity or enjoyment, these estimates should be interpreted as descriptive associations rather than as causal effects of remote work on enjoyment or productivity.

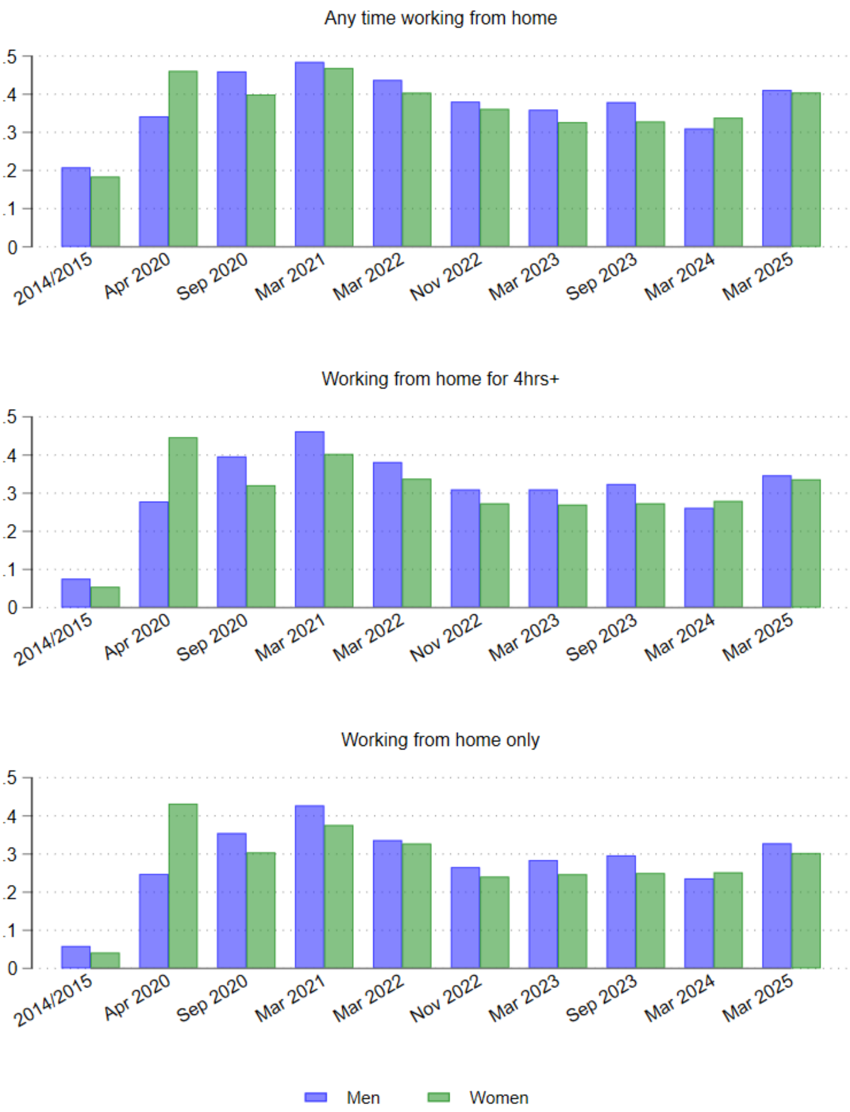
5. Results

To explore the evolution of working from home in time use data before, during, and after the pandemic we first compare the proportion of diaries that report time working from home in the UK TUS 2014/15 with the diaries in the OTUS waves. In Figure 2 we consider three definitions of "working from home" and look at the proportion of diaries reporting time corresponding to each definition: any time working from home during the 24 hours diary; at least 4 hours working from home; and only time working from home. Around 20% of all diaries report any time working from home in 2014/2015. This percentage increases sharply, and particularly for women, during the first COVID wave, when schools were closed – 46% of women and 35% of men report at least some time of remote work in April 2020. Diaries of male respondents reporting any remote work time increase over the following two waves, reaching 41% of the total in March 2021, while diaries of female respondents reporting any time working from home fluctuate (first decreasing in September 2020 and then increasing again in March 2021 to similar

[9] All regressions include the following set of individual characteristics: education levels, age, relationship status, number of children, ethnicity, house tenure, indicators for income bands, indicator for whether the respondent has a health condition, total workhours in the week.

levels as April 2020). In March 2022 and November 2022 (all) respondents are less likely to report time working from home than during the pandemic. Over the following four waves the percentage of diaries reporting any working from home hovers around 35%, with some minor and statistically insignificant fluctuations. We observe a slight uptick to 40% reporting any working from home in March 2025. This increase is consistent with US evidence for 2025 (Bureau of Labor Statistics, 2026).

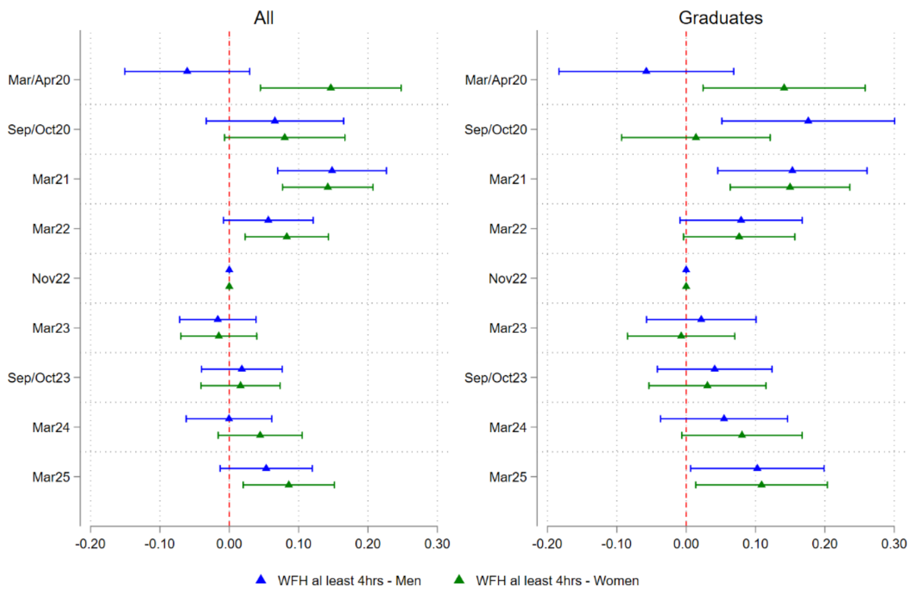
Figure 2: Extensive margin – Proportion of diaries reporting WFH



Notes: Data from the UK Time Use Survey 2014/15 and nine waves of OTUS time diary surveys (April 2020 to March 2025). Observations are diaries by all respondents in employment during a weekday reporting at least four hours of work. The three figures present the proportion of diaries by gender reporting working from home according to three definitions: any time working from home (top panel); at least four hours working from home (central panel) and working only from home (bottom panel). Survey weights are used in the calculation of proportions.

Considering more stringent definitions of time in remote work preserves the pattern observed over time, albeit at a lower rate. The percentage of diaries reporting at least 4 hours of working from home is 8% and 5% in 2014/15 (for men and women, respectively), peaking at 46% and 40% in March 2021 during the strictest lockdown of COVID pandemic, and then stabilising just below 30%, for both men and women, from November 2022 onwards with the exception of March 2025 when the proportion increases again to above 30%. The percentage of diaries reporting only time in paid work from home was around 5% for both men and women in 2014/15, 42% and 38% in March 2021 and around 25% for all respondents from November 2022 onwards again with the exception of March 2025 when this proportion increases again to above 30%.

Figure 3: Probability of diaries reporting WFH – differences across OTUS waves, all



Notes: the table reports estimates from two LPMs for the probability of diaries reporting time WFH at least four hours. Baseline category is wave 5, November 2022. Regressions include a comprehensive set of socio-demographic and economic characteristics of the respondents and they were estimated separately for men and women using diary weights. Robust standard errors in parenthesis.

After establishing a sustained shift in favour of working from home during the pandemic compared to before – a shift that persists through 2025 – we examine changes in the probability of reporting remote work across the OTUS waves, using a linear probability model with a comprehensive set of controls, as detailed in Figure 3. These estimates show the difference in the probability of reporting time in remote work across different waves of the OTUS data, with the baseline category here being November 2022 (the tail end of the pandemic period) for the full sample and for graduates. Contrasting the pandemic waves to the November 2022 baseline and focusing on more stringent definitions of working from home, we find that women report a higher rate of remote work at the start of the pandemic (April

2020 wave), in March 2021 (during the third lockdown) and March 2022. Men do not report a higher rate of remote work at the start of the pandemic but do report a higher rate in March 2021. For women the probability of reporting remote work doesn't change between November 2022 and March 2024 but increases in March 2025. From November 2022 to our latest survey wave in March 2025 there is no change in the probability of reporting remote work for men. The uptick in remote work in March 2025 for women and for graduate men and women suggests, if anything, that the shift to remote work may still be gaining traction.

In the reminder of this paper we will define respondents as remote workers if they report (at least four hours of paid work and) at least 4 hours working from home during the diary day; we will focus our analysis on the post-pandemic period November 2022 to March 2025, when the rate of remote working stabilised at a new norm. We will present results for the full sample and for the sample of university graduates as they are the group more likely to work from home.

Table 1 reports results from separate OLS regressions of time spent on each activity, with time in each activity regressed on an indicator for remote work, a female dummy, and their interaction term (as in equation 1). Regressions are estimated separately for the full sample and for university graduates over the period November 2022 to March 2025. All specifications include socio-economic and demographic controls, regional and occupation fixed effects, and robust standard errors.[10] The estimates in the table are expressed as percentage differences (columns 2 and 4) relative to the baseline represented by non-WFH workers' mean time by activity (columns 1 and 3). For men, the estimates are the coefficients on the WFH dummy; for women, this is the sum of the WFH dummy and the WFH×Female interaction term.[11] The dependent variable is minutes spent in different activity groups, with diary entries as the unit of observation. The OTUS data allow us to identify only the location of work activities on the diary day but do not report any information about how often the respondents work from home during the rest of the week. Therefore, our results cannot extrapolate how respondents allocate their time across the remainder of the week (Pabilonia and Vernon, 2022).

Working from home is associated with a different allocation of time across activities in the diary day. In the full sample, men and women who work from home respectively spend 36 and 20 minutes more

[10] The full list of controls is reported in table C1 in Appendix C.

[11] Full estimates and standard errors are reported in tables D1a and D1b in Appendix D. The gender coefficients indicate persistent differences in time use among individuals who work from the office (the baseline) at least four hours in the diary day. Compared to men, women spend 11 more minutes in personal care, engage in 23 additional minutes of unpaid work, 3 more minutes of unpaid care and 6 more minutes in social media/internet (columns 2, 4, 5, and 9). They also spend less time than men on paid work (−16 minutes), travel (−8 minutes), leisure (−13 minutes), and watching TV (−12 minutes). These gender gaps are largely consistent across samples (full sample and only graduates only).

sleeping or resting (7.5% and 4% more than office workers) and 66 and 55 fewer minutes on travel compared to those not working from home: at least 70% less transport time compared to men and women working from the office. Women working remotely spend around 9 minutes less than their counterparts in the office in personal care (around 10% less time). Time spent on unpaid work increases by 26 and 23 minutes for respondents working from home, that is respectively 38% and 24% more minutes than respondents working from the office; similarly time spent in unpaid care is higher by 7 minutes for both men and women (over 45% more compared to the baseline) while no significant change is observed in time spent on leisure or social media. Women working from home watch more television than similar respondents working from the office: 9 minutes more, that is around 10% more time compared to the baseline. Men working from home spend marginally less time – 21 minutes – in paid work: 4.2% less compared to on-site workers. Thus, it would appear that for men, remote work has been associated with some substitution of unpaid work for paid work. Finally, both men and women report spending more time in well-being-related leisure—11 and 8 additional minutes, respectively—which is roughly double the amount of time office workers spend on the same activity.

These patterns are qualitatively similar for men and women in the graduate sample, although the reduction in travel time is slightly larger (−71 and −61 minutes) than in the full sample. The increase in sleep is similar for men in the full and graduate samples. The increase in sleep for graduate women (27 minutes or 5.7% more compared to the baseline) is a little higher than estimated for women in the full sample. In this sample, there is no difference in time spent on paid work between remote and on-site male workers, whereas women working from home report spending around 3% less time on this activity compared to the baseline. Overall, the findings indicate that WFH leads to substantial time savings in commuting and modest increases in home production. Gender differences in time allocation remain pronounced but working from home does not appear to amplify or reduce them significantly.[12]

[12] Results using a sample with no missing occupation information are reported in Appendix Table E1 and are qualitatively similar.

Table 1: Working from home and time across different main activities (November 2022-March 2025

	(1)	(2)	(3)	(4)
	Men: Baseline (On-site)	Men: WFH (%)	Women: Baseline (On-site)	Women: WFH (%)
		Full sample		
Sleeping	482.027	**7.54**	494.654	**4.05**
Personal care	112.987	-2.31	123.431	**-9.81**
Travel	85.461	**-76.76**	76.901	**-71.35**
Unpaid work	67.141	**38.22**	93.693	**24.48**
Unpaid care	14.823	**46.52**	16.188	**45.19**
Watching TV	96.899	-0.57	86.845	**10.61**
Leisure	45.097	3.67	37.789	10.4
Wellbeing / fitness	11.001	**98.28**	10.548	**79.77**
Social media / Internet	28.134	21.75	35.861	7.3
Paid work	487.559	**-4.28**	453.441	-1.2
N	1489	700	1512	685
		Graduates		
Sleeping	472.947	**7.39**	481.503	**5.67**
Personal care	113.741	-0.39	119.361	**-8.18**
Travel	94.866	**-75.87**	85.831	**-71.05**
Unpaid work	68.34	**36.69**	86.586	**33.29**
Unpaid care	19.55	**49.46**	20.205	**38.11**
Watching TV	90.113	-0.62	86.01	**9.83**
Leisure	46.47	-9.09	40.985	-1.39
Wellbeing / fitness	12.841	**90.39**	12.02	**89.77**
Social media / Internet	34.135	8.53	37.647	13.95
Paid work	480.309	-1.9	463.478	**-3.2**
N	711	496	782	469

Notes: The WFH(\%) columns report coefficients from OLS regressions expressed as percentage differences relative to non-WFH workers. For men, this is the coefficient on the WFH dummy; for women, this is the sum of the WFH dummy and the WFH×Female interaction term. The dependent variable is minutes spent in different activity groups, with diary entries as the unit of observation. All regressions include demographic and socio-economic controls, occupation and region fixed effects, and are estimated using survey weights. Robust standard errors in parentheses. Bold estimates are significant at the 1% level. The large percentage changes for well-being and fitness activities reflect a near-zero baseline for on-site workers (approximately 11 minutes); the absolute minute differences for these rows are more informative.

Figures 4a (for the full sample) and 4b (for the graduate sample) plot the 95% confidence interval of the probability of engaging in paid work over 24 hours for men and women, separately by work location—working from home (blue shaded area) and working away from home (orange shaded area). These are estimates from a linear probability model with individual fixed effects and hour dummies, where the baseline is midnight. The green area displays the difference in work probability between the two groups (the coefficients for the interaction terms between hours and the remote work indicator). The diurnal structure of work is clearly evident in both panels, with activity concentrated between 8:00 and 18:00. However, working from home substantially reshapes the daily work pattern for both men and women. Among both genders remote workers are less likely to work early in the morning (8:00–10:00) and early afternoon (12:00–13:00), while they are more likely to work in late afternoon (16:00-17:00). This pattern is consistent with the greater temporal flexibility afforded by remote work.

While the overall pattern holds for both genders, the magnitude of adjustment appears larger for men, particularly in the morning peak, where the probability of working falls notably for the remote work group relative to the working away from home group. For women, the shift away from conventional hours is also present but less pronounced.

These findings suggest that working from home facilitates a redistribution of work time away from office norms, and that men may be more responsive to this flexibility. This aligns with prior evidence that remote work reduces commuting constraints and may enable better alignment of work with personal schedules within the workday. The gender difference in responsiveness could also reflect gendered constraints at home (e.g., caregiving or domestic responsibilities) that continue to shape women's daily routines whether working in the office or remotely.

An important question with implications for work productivity is whether people working from home are more likely to engage in multitasking while working. We answer this question by looking at differences in time spent in reported secondary activities - activities conducted simultaneously with a primary activity, in this case paid work – between individuals working from home and away from home.

Figure 4a: Probability of being in work over 24 hours – All, November 2022-March 2025

Figure 4b: Probability of being in work over 24 hours – Graduates, November 2022-March 2025

Notes: These figures show the 95% confidence intervals of the estimated probability of engaging in paid work by hour of the day for graduates only, separately for women (left panel) and men (right panel), comparing those working from home (blue line) and those working away from home (orange line). The green shaded area depicts the 95% confidence intervals of the difference between the two groups. These probabilities are derived from a linear probability model estimated separately by gender, where the dependent variable is an indicator for whether the respondent is working at a given time. The model includes hour-of-day fixed effects, an indicator for working from home, their interaction, and individual fixed effects. Estimates are based on 24-hour time-use diary data.

Table 2 examines how remote work affects time spent on *secondary* activities - activities conducted simultaneously with a primary activity - such as secondary childcare or leisure, across both the full sample and the graduate sub-sample. Each column presents results from separate regressions, controlling for gender, remote work status, their interaction, as well as a set of demographic and socio-economic characteristics. All specifications include socio-economic and demographic controls, regional and occupation fixed effects, and robust standard errors. As in the previous table, estimates are expressed as percentage differences (columns 2 and 4) relative to the baseline represented by non-WFH workers' mean time by activity (columns 1 and 3).[13]

Among all individuals, working from home is associated with more than twice the amount of time spent on all types of leisure secondary activities by office workers (+20 and +17 minutes, respectively for men and women) and on secondary unpaid work and care (+4 minutes) only for women. A similar pattern is observed among graduates only. Overall, these results indicate that working from home facilitates multitasking with leisure and care/housework activities. It does not appear to significantly increase time spent in other secondary activities.

Table 2: Time in secondary activity while at work 2022-2025

	(1) **Men: Baseline (On-site)**	(2) **Men: WFH (%)**	(3) **Women: Baseline (On-site)**	(4) **Women: WFH (%)**
		Full sample		
Sleeping + personal care	10.84	10.69	10.09	15.1
Unpaid work + unpaid care	2.33	137.77	3.11	**125.02**
Watching TV + leisure + wellbeing	15.83	**125.81**	13.03	**132.62**
Social media + internet browsing	12.69	8.98	10.91	-0.49
N	1489	700	1512	685
		Graduates		
Sleeping + personal care	11.099	11.01	11.121	35.81
Unpaid work + unpaid care	3.448	86.42	3.451	**125.10**
Watching TV + leisure + wellbeing	15.137	**148.70**	11.537	**143.90**
Social media + internet browsing	11.265	29.31	11.633	12.92
N	711	496	782	469

Notes: the table reports the estimates from a set of OLS regressions where the dependent variable is number of minutes spent in different groups of secondary activities while the primary activity is paid work and the unit of observation is diaries. Regressions include a comprehensive set of socio-demographic and economic characteristics of the respondents and they were estimated using diary weights. Robust standard errors in parenthesis. The top panel report results for the sample including all individuals, the bottom panel reports results of regressions for graduates.

So far we have observed that working from home in the post pandemic years is associated with a re-allocation of time within the working day and greater multitasking. To build on the evidence of time reallocation, the next set of results explores the (subjective) wellbeing implications of working from home. In particular, we examine whether working from home is associated with differences in individuals' enjoyment of specific activities, starting from paid work, and whether this working

[13] Full estimates and standard errors are reported in table D2 in Appendix D. Gender differences in the baseline (individuals working from the office) are not statistically significant.

arrangement has spillover effects on the enjoyment of other domains of daily life. This analysis is motivated by the idea that changes in how time is allocated may not fully capture the wellbeing consequences of remote work. To address this, we leverage data on individuals' time allocation alongside self-reported enjoyment levels on a seven-point scale for each activity.

First of all, we estimate differences in instantaneous enjoyment across activities, distinguishing between remote work and work conducted outside the home. This analysis is conducted November 2022–March 2025 using a regression framework at the episode level, controlling for episode length and individual fixed effects (as in equation 2). The baseline category for these estimates is sleeping and personal care, as they are activities which appear in all diaries. Figures 5a and 5b illustrates that respondents in the full sample and in the sample of university graduates report higher enjoyment when working from the office than when working from home. One additional result to highlight from these figures is that travelling is one of the least liked activities when compared to sleeping and personal care both, in the full sample and in the subsample of graduates.

It is however possible that remote work relates to the enjoyment of (or ability to undertake) other activities, such as leisure and unpaid work, for instance by reducing the stress and time constraints associated with commuting. To explore this further, we estimate differences in enjoyment between remote and office-based workers across key activity categories, including personal care, leisure, housework, unpaid care, and travel. Table 3 presents the results for the full sample (top panel) and for graduates only (bottom panel). Among the full sample and the subsample of graduates, respondents working from home report lower enjoyment in undertaking unpaid care than respondents who work away from home and more enjoyment in travelling. Women also report lower enjoyment in sleeping (only in the full sample) and higher in unpaid work. Among graduates, men who work from home report lower enjoyment of wellbeing and fitness activities than men who work away from home, while women who work from home report higher enjoyment in general leisure compared to women who work away from the home.

Figure 5a: Preferences (Instantaneous enjoyment) over activities – All, 2022-2025

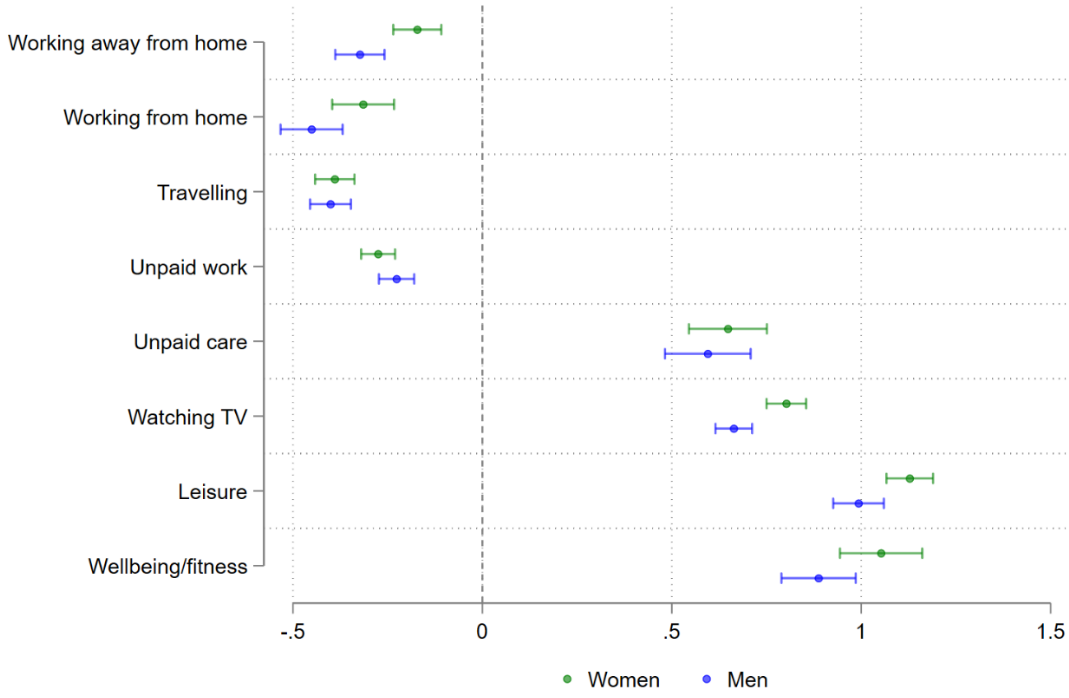
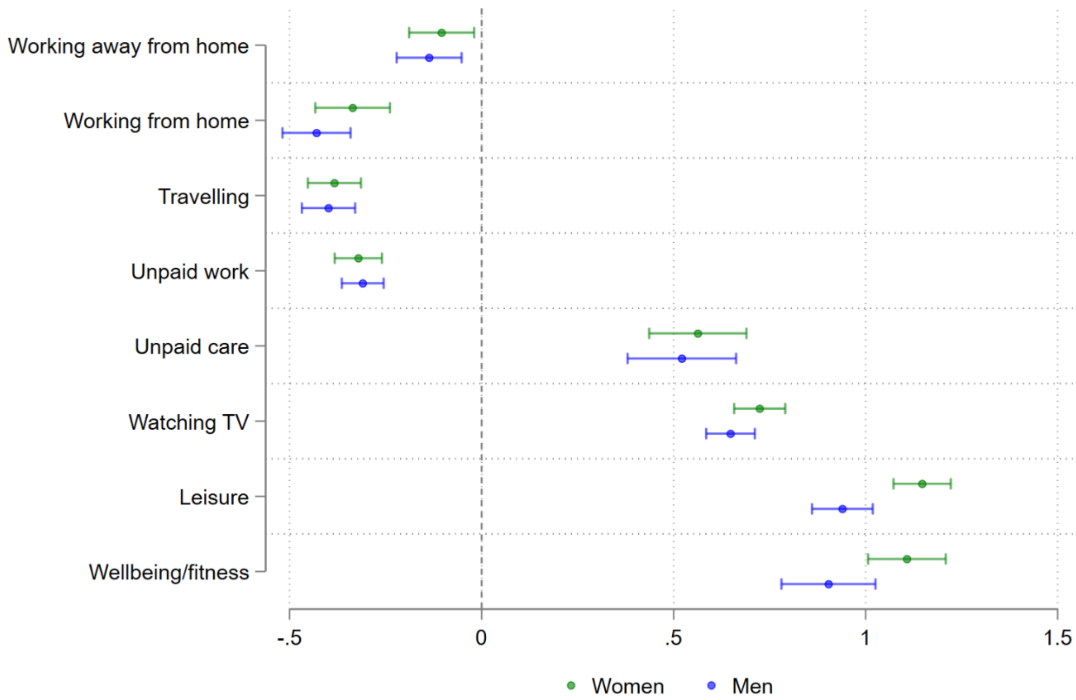


Figure 5b: Preferences over activities – Graduates, 2022-2025



Notes: the figure reports coefficients and 95% confidence intervals from regressions estimated by gender at the episode level of instantaneous enjoyment, on episode length and individual fixed effects. The baseline category for these estimates are sleeping and personal care, as they are activities that appears in all diaries. Data from November 2022-March 2025

Table 3: Enjoyment in other main activities – 2022-2025

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sleeping	Personal care	Travel	Unpaid work	Unpaid care	Watching TV	Leisure	Wellbeing/ Fitness
					All			
Constant	5.013***	5.424***	4.782***	5.115***	5.587***	5.384***	5.885***	6.152***
	(0.211)	(0.125)	(0.171)	(0.158)	(0.444)	(0.242)	(0.321)	(0.474)
Female	-0.063	0.057*	-0.038	0.008	0.092	0.127**	0.154**	0.137
	(0.051)	(0.029)	(0.039)	(0.039)	(0.094)	(0.052)	(0.066)	(0.098)
WFH	0.004	-0.013	0.150***	0.017	-0.160*	0.027	-0.079	-0.148
	(0.056)	(0.034)	(0.058)	(0.045)	(0.095)	(0.058)	(0.088)	(0.104)
WFH*Female	-0.107	0.062	0.054	0.076	0.001	0.028	0.171	0.156
	(0.079)	(0.046)	(0.077)	(0.058)	(0.127)	(0.079)	(0.108)	(0.140)
WFH+ WFH*Female	-0.102*	0.0489	0.204***	0.093**	-0.158*	0.054	0.092	0.008
	(0.059)	(0.033)	(0.053)	(0.040)	(0.088)	(0.056)	(0.070)	(0.099)
N	9674	17513	8604	12414	1994	4187	2670	1178
R^2	0.03	0.028	0.047	0.017	0.088	0.039	0.061	0.099
					Graduates			
Constant	5.156***	5.639***	5.124***	5.113***	4.939***	5.794***	5.773***	5.926***
	(0.281)	(0.161)	(0.206)	(0.211)	(0.549)	(0.314)	(0.432)	(0.417)
Female	-0.057	0.061	-0.020	0.013	0.057	0.107*	0.109	0.128
	(0.066)	(0.038)	(0.052)	(0.052)	(0.115)	(0.063)	(0.083)	(0.123)
WFH	0.016	-0.011	0.086	0.001	-0.264**	-0.007	-0.148	-0.242**
	(0.067)	(0.043)	(0.070)	(0.055)	(0.115)	(0.074)	(0.108)	(0.121)
WFH*Female	-0.060	0.072	0.157*	0.049	0.026	0.029	0.318**	0.324*
	(0.095)	(0.056)	(0.092)	(0.070)	(0.154)	(0.094)	(0.128)	(0.170)
WFH+ WFH*Female	-0.044	0.061	0.243***	0.050	-0.238**	0.021	0.169**	0.082
	(0.071	(0.039)	(0.062)	(0.047)	(0.104)	(0.067)	(0.082)	(0.121)
N	5539	9978	4804	7315	1416	2258	1676	800
R^2	0.037	0.046	0.075	0.021	0.102	0.059	0.1	0.103

Notes: Data from five waves of OTUS time diary surveys (March 2022 to March 2025). Observations are episodes of activities reported in diaries by respondents in employment during a weekday. The dependent variable is defined as the instantaneous enjoyment reported by respondents for each episode. Controls include socio-demographic characteristics of the respondents (age, marital status, household size, household income, number of children by age group) and a set of region dummies.

Finally, we investigate whether remote workers perceive their working time as more productive. To address this question, we utilize the experimental measure of self-perceived productivity that we collected in the two most recent waves of the OTUS time-use diaries from March 2024. Each time respondents recorded a period of paid work in their diary, they were asked to assess their productivity on a five-point scale, as well as their enjoyment on a seven-point scale.

Figure C1, Appendix C, shows the distribution of this measure for remote and office workers and for the full sample (top panels) and for the subsample of only graduates (bottom panels). Office workers are more likely to report the highest level of self-perceived productivity (productive at 100%) compared to respondents working from home. Figure C2 presents in parallel the distribution of instantaneous enjoyment of paid work, where office workers are more likely to report higher enjoyment. Table 4 presents estimates of the differences in self-reported productivity and enjoyment between remote and office-based workers (as per equation 3). Results are reported separately for the full sample (N≈2,937; top panel) and for graduates only (N≈1,650; bottom panel), covering March 2024 and March 2025 only. Self-reported productivity is analysed both as a continuous measure (column 1) and as a dichotomous variable with varying cut-offs (columns 2–4, respectively where self-reported productivity equals 3 or more, equals 4 or more and equals 5, the highest level of productivity). Finally, column 5 reports the estimated difference in instantaneous enjoyment for the same work episodes.

Women, on average and keeping everything else constant, report higher self-perceived productivity than men across all estimates. Respondents who report working from home in their time-use diaries perceive their time to be less productive (column 1). This effect is primarily driven by a lower likelihood of reporting the highest level of productivity (Productivity = 100%; column 5) and is evident both in the full sample and in the subsample of graduates. In the full sample, both men and women working from home are 5 percentage points less likely to report the highest productivity level, relative to on-site workers, among whom 22% of men and 25% of women report this outcome. The difference is more pronounced among graduates: male and female graduates working from home are respectively 10 and 7 percentage points less likely to report the highest productivity level, compared with baseline rates of 16% and 18% among their on-site counterparts.

These findings should be interpreted as descriptive associations. In particular, it is possible that workers select WFH days for tasks that are intrinsically less stimulating or that require less intensive effort. Evidence from companion research using public sector time-use diaries suggests that WFH days are indeed characterised by a substantial reallocation towards administrative and coordination activities and away from sector-specific tasks (Foliano, Riley and Tonei, mimeo). If so, the lower enjoyment and perceived productivity observed on WFH days would partly reflect task composition rather than the effect of the work location itself. The OTUS diaries do not record task content, so this alternative explanation cannot be ruled out.

Gender differences emerge consistently across all dimensions of the analysis. Men increase their time on unpaid activities by a larger percentage than women on WFH days, yet the absolute gender gap in unpaid work remains, because women's baseline level of unpaid work is substantially higher. The timing flexibility of paid work is also more pronounced for men, who redistribute a larger share of work episodes away from standard hours. For enjoyment and self-perceived productivity, the estimated gaps between WFH and on-site work are slightly smaller for women than for men. Together, these patterns suggest that WFH generates modest and asymmetric changes in gendered time use: men gain more temporal flexibility and expand their contribution to domestic activities, but the structural inequality in unpaid work remains broadly intact.

5. Summary and Conclusions

This paper explores novel time use diary data to study the step shift in remote work that was instigated by the COVID-19 pandemic. We document the sustained transformation in remote work patterns in the UK since the end of the pandemic and validate trends in remote work observed from representative time use diaries against trends observed in traditional population surveys. The sustained proportion of diaries reporting home-based work from two years after the pandemic up to March 2025 suggests that many workers, and possibly employers, perceive remote work as a viable and often preferable alternative to traditional office-based arrangements.

Table 4: Self perceived productivity

	(1)	(2)	(3)	(4)	(5)
	OLS		Probit		OLS
	Productivity	Pr(Prod>=80%)	Pr(Prod>=90%)	Pr(Prod=100%)	Enjoyment
			All		
Female	-0.125*	-0.005	-0.052*	-0.051**	-0.279***
	(0.070)	(0.023)	(0.031)	(0.024)	(0.077)
WFH	0.158***	0.060***	0.067**	0.021	0.021
	(0.060)	(0.021)	(0.027)	(0.020)	(0.067)
WFH*Female	0.113	0.034	0.047	-0.001	0.132
	(0.091)	(0.032)	(0.041)	(0.033)	(0.105)
WFH+WFH*Female	-0.0124	0.0287	-0.00466	-0.0515	-0.147
	(0.064)	(0.024)	(0.030)	(0.023)	(0.082)
N	2937	2937	2937	2937	2937
Baseline men		0.811	0.491	0.220	
Baseline women		0.853	0.584	0.250	
R^2	0.097				0.110
			Graduates		
Female	-0.208**	-0.011	-0.065*	-0.100***	-0.297***
	(0.085)	(0.031)	(0.039)	(0.026)	(0.094)
WFH	0.142*	0.053*	0.082**	0.020	0.046
	(0.084)	(0.031)	(0.037)	(0.023)	(0.094)
WFH*Female	0.168	0.035	0.052	0.032	0.006
	(0.117)	(0.043)	(0.053)	(0.037)	(0.129)
WFH+WFH*Female	-0.0399	0.0238	-0.0133	-0.0685	-0.291
	(0.083)	(0.032)	(0.037)	(0.025)	(0.096)
N	1650	1650	1650	1650	1650
Baseline men		0.777	0.418	0.158	
Baseline women		0.826	0.525	0.183	
R^2	0.134				0.155

Notes: Data from March 2024-March 2025 (waves 8 and 9). Observations are episodes of activities reported in diaries by graduate respondents in employment during a weekday. The dependent variable is defined as the self-perceived productivity reported by respondents for each episode. Values are: 5 = 100% productive; 4 = 90-99% productive; 3 = 80-89% productive; 2 = 70-79% productive; 1 = Less than 70% productive. Column1 reports estimates from an OLS regression, columns 2 to 4 report marginal effects from a set of estimated probit where the dependent variable is defined by different cut-offs respectively as: equal 3 or more, equal 4 or more and equal 5. Finally column 5 reports estimates from an OLS regression where the dependent variable is instantaneous enjoyment reported during paid work. Controls include socio-demographic characteristics of the respondents (age, marital status, household size, household income, number of children by age group) and a set of region dummies. Estimates reported for probit models are marginal effects.

Our analysis of time-use reveals the factors influencing workers' preferences for remote working. Remote workers allocate the time saved from commuting to activities that are typically ranked higher on the enjoyment scale. This includes sleep, well-being and fitness activities, as well as unpaid caring activities. Remote workers also allocate some of the time freed up from less commuting to unpaid (house)work. For men, remote work is associated with some substitution of unpaid work for paid work. Our results also reveal that remote workers and on-site workers spread their working time differently across the day. Compared to on-site workers, remote workers are less likely to work early in the morning and during lunchtime, and more likely to work late afternoon, consistent with the greater temporal flexibility afforded by remote work. Remote workers spend more working time in combination with other activities that they enjoy more (leisure and well-being activities). These patterns provide some evidence as to why remote working has been sustained and why workers are willing to accept a pay cut (Barrero et al, 2021) or lower wage growth (De Fraja et al, 2024) in order to work remotely.

We provide novel insight into the relationship between remote working, instantaneous enjoyment and self-perceived productivity. We find that time spent in work is perceived as both less enjoyable and less productive when conducted remotely rather than on-site. This contrasts with evidence from surveys (Barrero et al, 2021). Compared to surveys our data minimize recall bias and are less influenced by social desirability bias. The differences in perceived productivity and enjoyment that we observe between remote and on-site working are particularly pronounced for graduates and are greater for men than for women. These findings reinforce that it is commuting avoidance and the flexibility afforded by remote work, rather than the location of work in and of itself, that underpins worker preferences for remote work.

Our study highlights the complex interplay between work location, time use, and economic trade-offs, reinforcing the need for nuanced discussions around the future of work. It complements recent research exploring the trade-offs workers face when choosing remote work, particularly in relation to productivity, mental well-being, and long-term career development (Emanuel and Harrington, 2024; Gibbs et al., 2023; Denzer and Grunau, 2024; De Fraja et al, 2022). It raises important questions for employers and policymakers alike. Employers considering hybrid or fully remote work arrangements might consider that remote work is not inherently more enjoyable or indeed productive, but is valued by workers primarily for the flexibility and cost savings it offers. Policymakers aiming to support workers in a remote-first world may need to focus on improving the infrastructure for home-based work and rethinking urban commuting policies to make in-office work more attractive.

The relationships we uncover between enjoyment, perceived productivity and the location of work might arise because of differences in tasks carried out at home and on-site or other unmeasured selection. Larger scale time diaries carried out over multiple workdays and distinguishing in-work tasks would provide a helpful tool for future research into the relationship between productivity and the location of work.

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Appendix A – Additional APS results

Figure A1: Proportion working from home – occupations

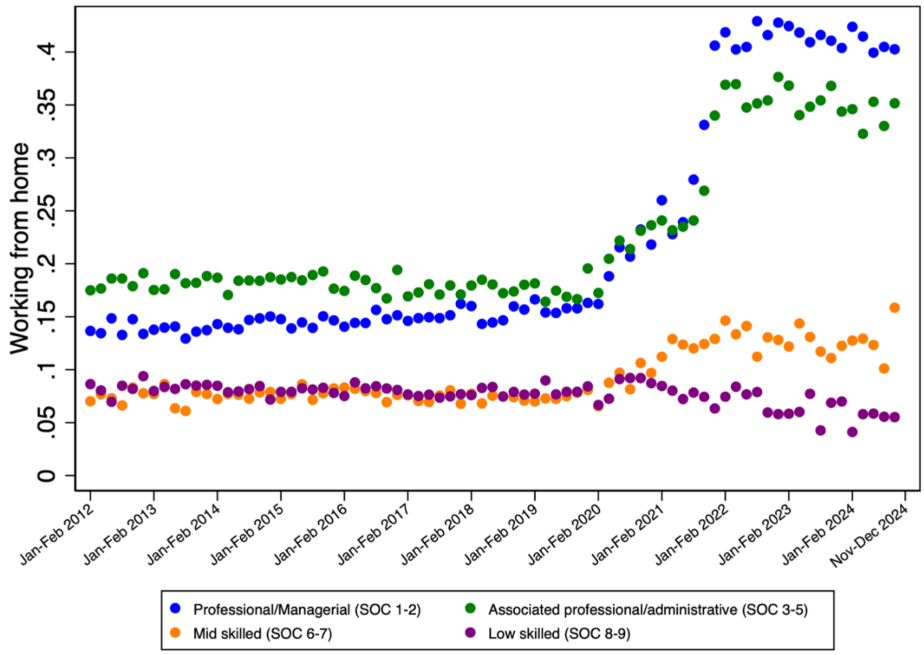
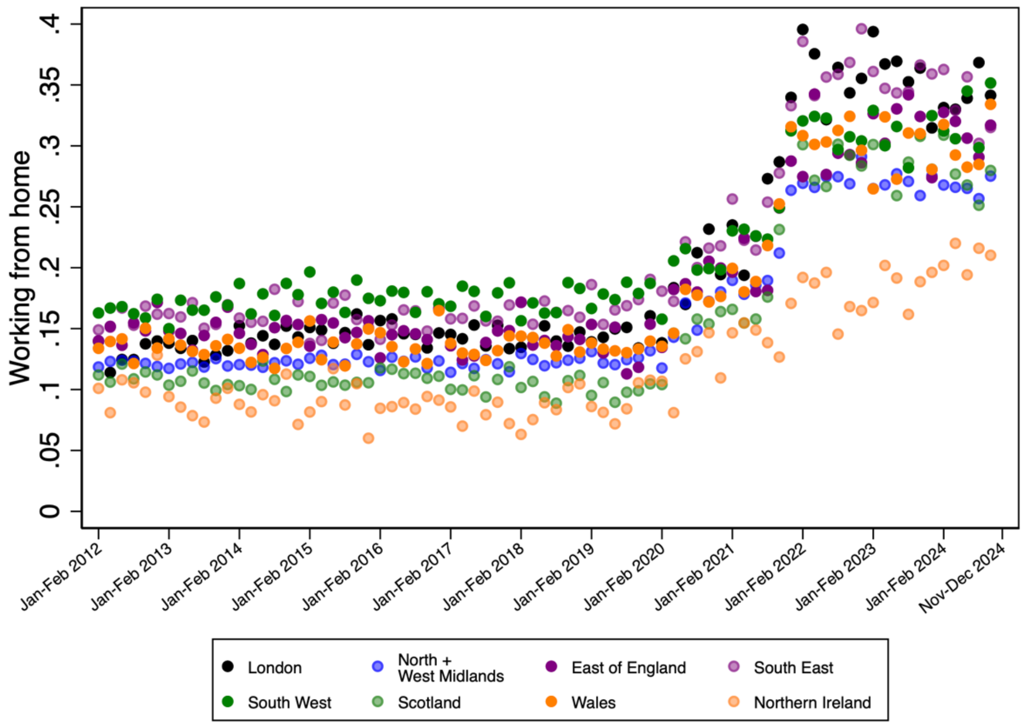
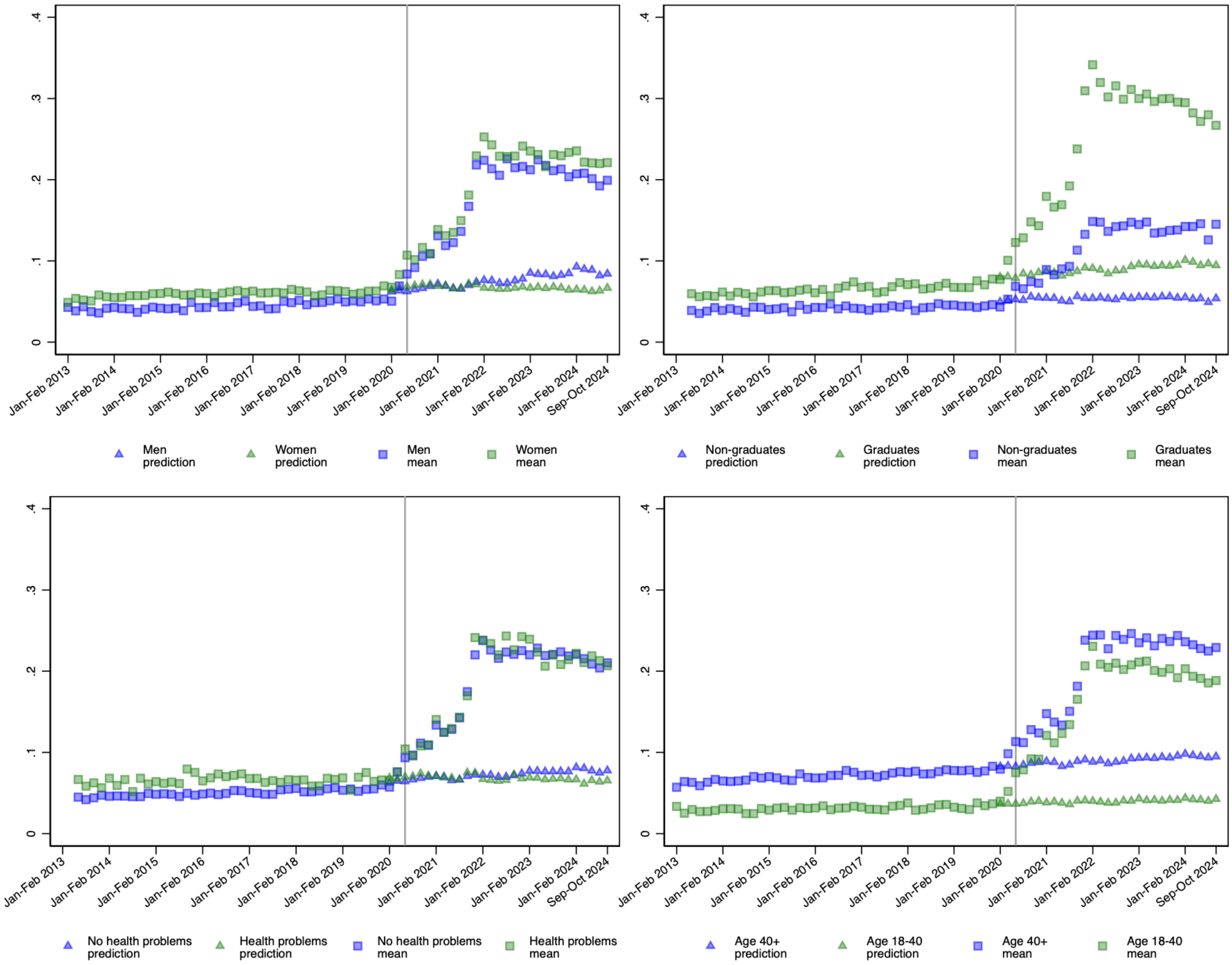


Figure A2: Proportion working from home – regions



Notes: APS data 2012-2024, sample weights used.

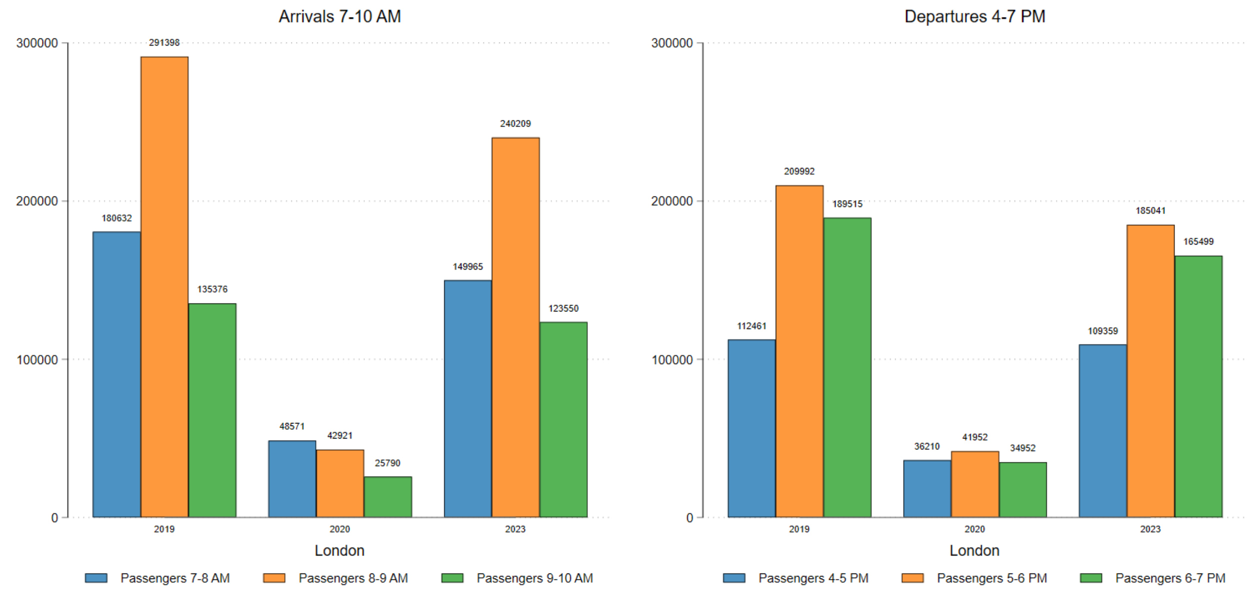
Figure A3: Proportion working *mainly* from home



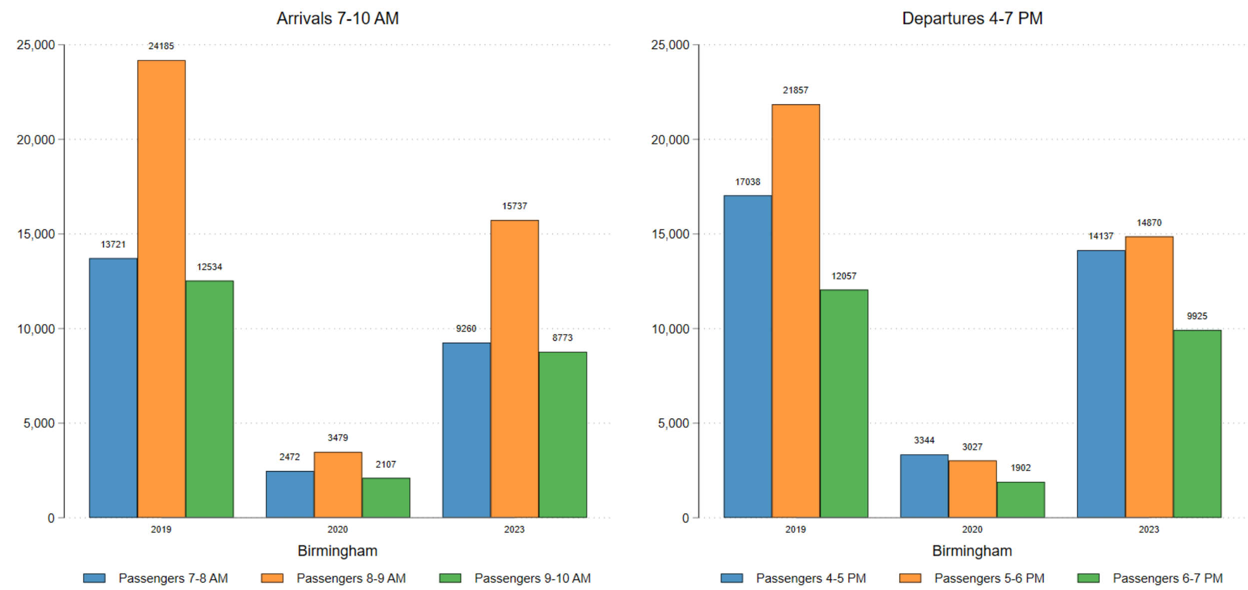
Notes. The figure shows the bi-monthly proportion (square markers) of respondents working *mainly* from home and the prediction out of sample (triangle markers) for the period January 2020 – September/October 2024 based on APS data. Predicted proportion of WFH for the years 2020 - 2024 was obtained by first estimating, separately by sub-sample, a probit for the reported working *mainly* from home on age, highest qualification, economic activity, occupations, region of residence, marital or cohabiting status, a time trend, a squared and cubic time trend and month dummies for the years 2012-2019 and then averaging the out-of-sample individual predictions by sub-sample and time. Predictions and means are obtained using the individual weights provided in the APS.

Figure A4: Train passengers flows during rush hours: London, Birmingham and Manchester

(a) London



(b) Birmingham



(c) Manchester

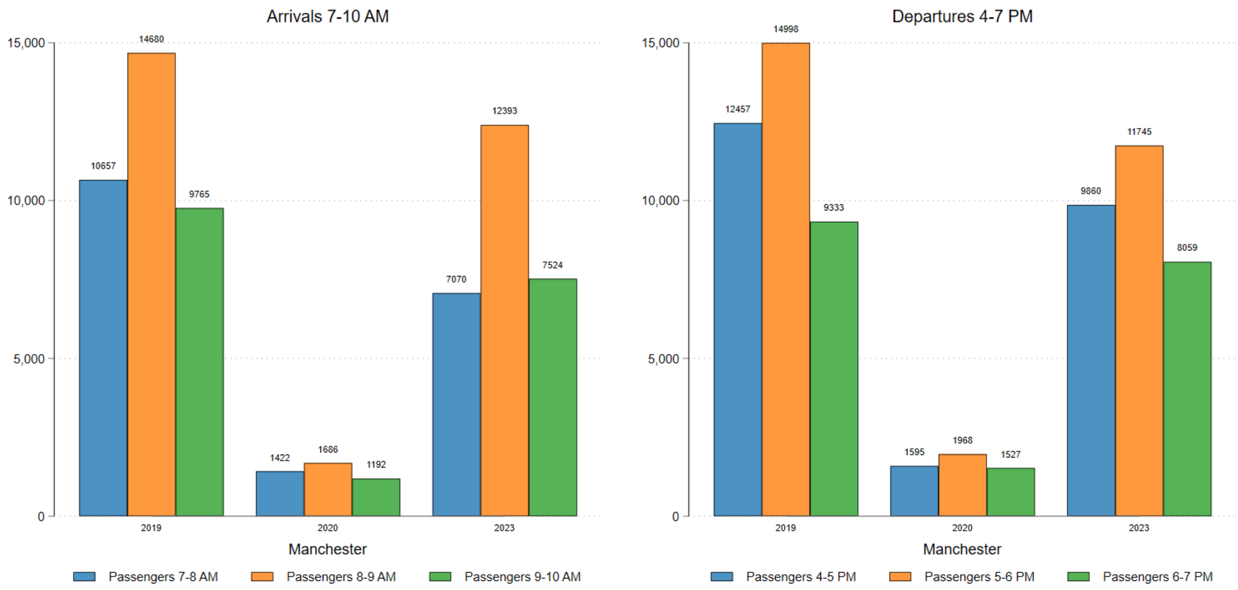
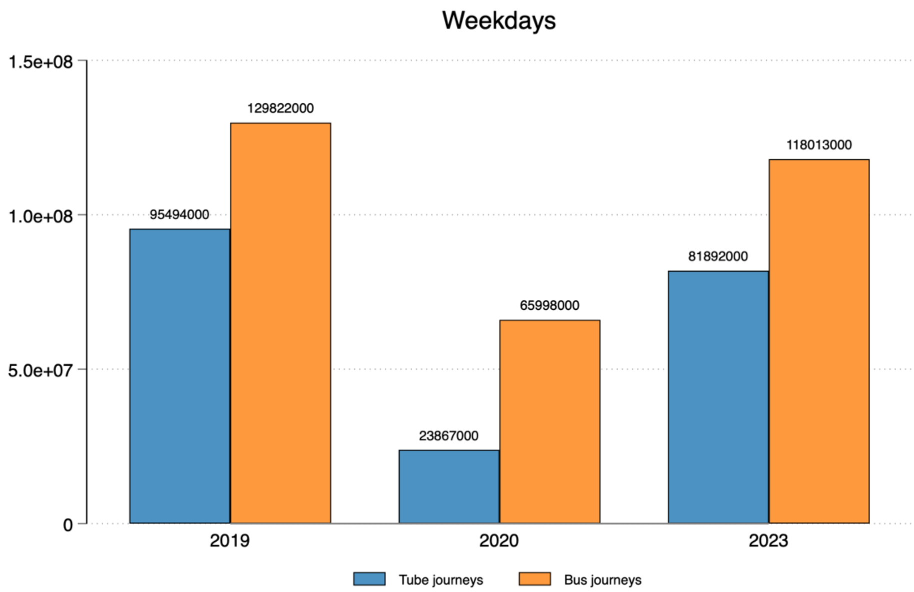


Figure A5: TFL journey counts



Note: total weekday journeys for buses and underground in November 2019, 2020 and 2023 in London as recorded by TFL. Data available from: https://tfl.gov.uk/corporate/publications-and-reports/network-demand-data

Appendix B: OTUS interface

Figure B1: OTUS instrument

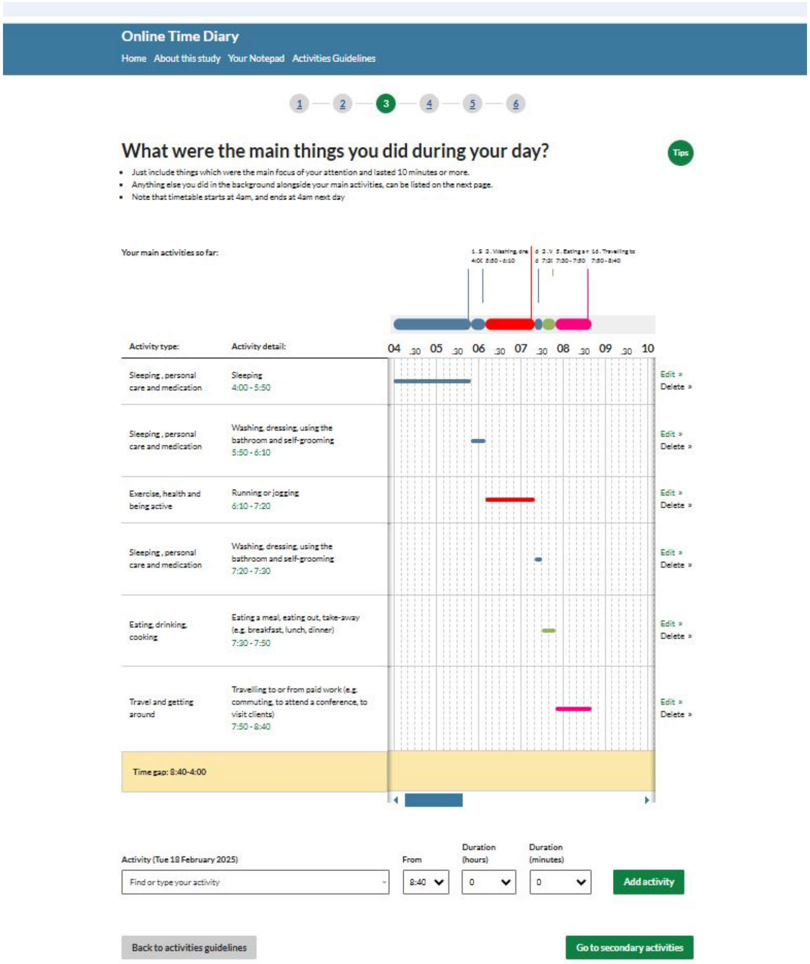
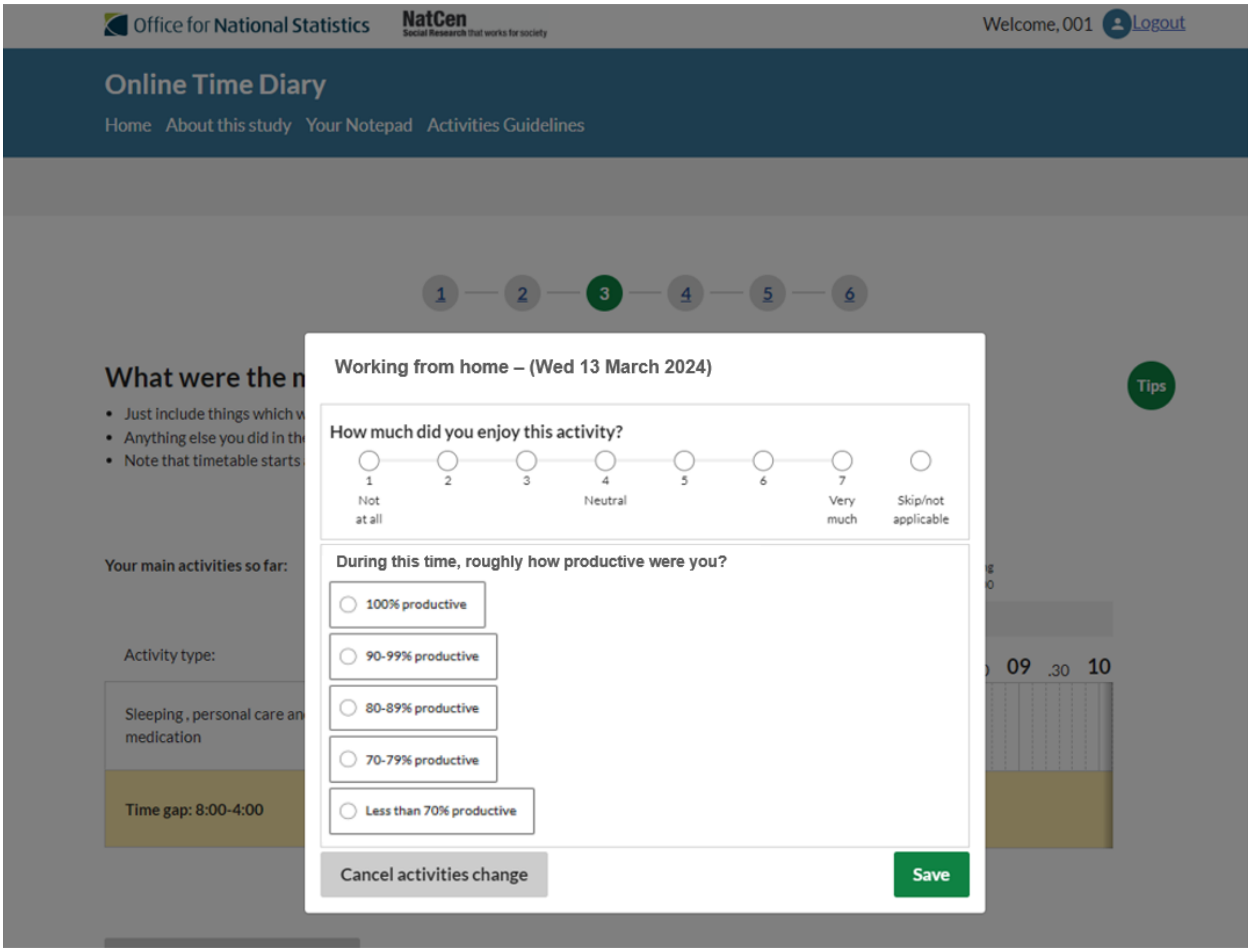
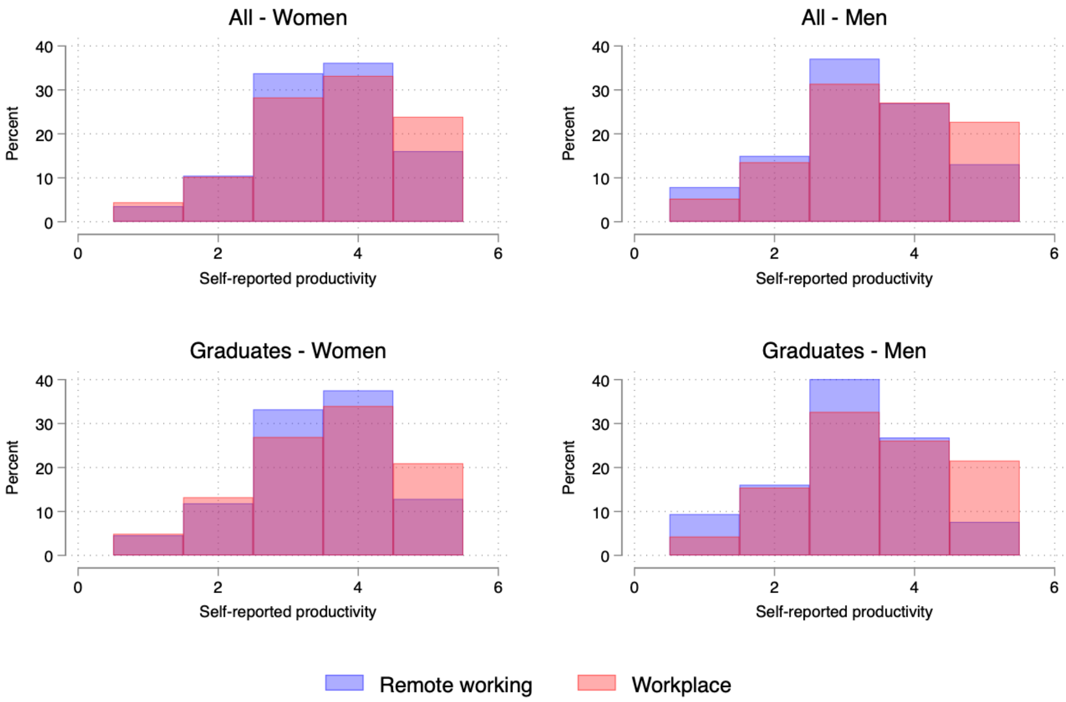


Figure B2: OTUS Wave 8 – Self-reported productivity



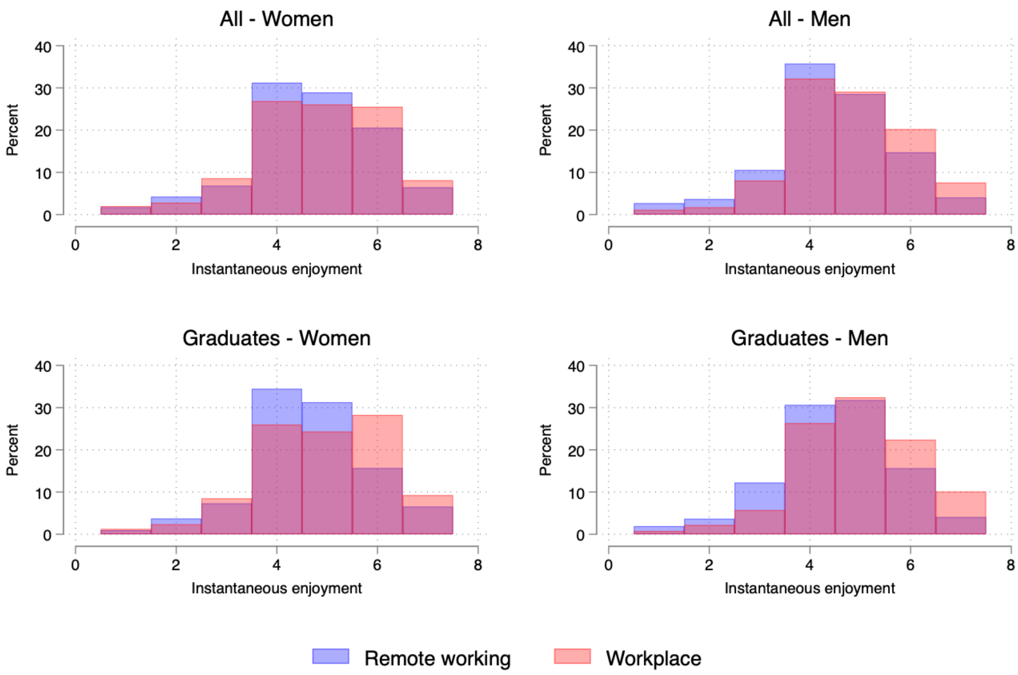
Appendix C: OTUS data

Figure C1: Self-reported productivity – March 2024 and March 2025



Notes: the figures report the weighted distribution of the measure of self-reported productivity for the full sample and for graduates. Values of the measure are: 5 = 100% productive ; 4 = 90-99% productive ; 3 = 80-89% productive ; 2 = 70-79% productive ; 1 = Less than 70% productive.

Figure C2: Instantaneous enjoyment in work – March 2024 and March 2025



Notes: weighted measure of enjoyment on a seven-point scale (1=lowest enjoyment, 7=highest enjoyment) across all episodes in the 2024 and 2025 waves of OTUS data.

Table C1: Summary Statistics of socio-economic characteristics in OTUS data

	Waves				
	Nov 2022	*Mar 2023*	*Sep 2023*	*Mar 2024*	*Mar 2025*
WFH	0.315	0.327	0.303	0.286	0.346
	(0.465)	(0.469)	(0.460)	(0.452)	(0.476)
Female	0.535	0.513	0.475	0.494	0.482
	(0.499)	(0.500)	(0.500)	(0.500)	(0.500)
College degree	0.606	0.606	0.523	0.498	0.545
	(0.489)	(0.489)	(0.500)	(0.500)	(0.498)
GCSE-A level	0.348	0.353	0.422	0.447	0.406
	(0.476)	(0.478)	(0.494)	(0.497)	(0.491)
Other or no qual.	0.0464	0.0406	0.0544	0.0549	0.0492
	(0.211)	(0.197)	(0.227)	(0.228)	(0.216)
Age: less than 34	0.217	0.207	0.213	0.258	0.208
	(0.413)	(0.405)	(0.410)	(0.438)	(0.406)
Age: 35 to 44	0.253	0.281	0.260	0.245	0.279
	(0.435)	(0.450)	(0.439)	(0.430)	(0.449)
Age: 45 to 55	0.277	0.266	0.285	0.262	0.239
	(0.448)	(0.442)	(0.452)	(0.440)	(0.427)
Age: 55+	0.252	0.245	0.241	0.235	0.274
	(0.435)	(0.430)	(0.428)	(0.424)	(0.446)
Single	0.434	0.432	0.419	0.402	0.419
	(0.496)	(0.496)	(0.494)	(0.491)	(0.494)
With health condition	0.271	0.300	0.324	0.298	0.298
	(0.445)	(0.458)	(0.468)	(0.458)	(0.458)
House owner	0.723	0.720	0.688	0.678	0.684
	(0.448)	(0.449)	(0.464)	(0.468)	(0.465)
Hh size:	0.115	0.133	0.123	0.0999	0.133
	(0.320)	(0.340)	(0.329)	(0.300)	(0.340)
Hh size:	0.350	0.353	0.293	0.332	0.326
	(0.477)	(0.478)	(0.456)	(0.471)	(0.469)
Hh size:	0.433	0.419	0.473	0.463	0.442
	(0.496)	(0.494)	(0.500)	(0.499)	(0.497)
Hh size:	0.102	0.0950	0.110	0.105	0.0983
	(0.302)	(0.293)	(0.313)	(0.307)	(0.298)
Workhours: <30	0.171	0.151	0.178	0.0474	0.0562
	(0.376)	(0.358)	(0.382)	(0.213)	(0.230)
Workhours:>=30 &<=40	0.551	0.573	0.556	0.0499	0.0520
	(0.498)	(0.495)	(0.497)	(0.218)	(0.222)
Workhours:>40	0.243	0.231	0.233	0.903	0.892
	(0.429)	(0.421)	(0.423)	(0.297)	(0.311)
N of Children age 0-4	0.108	0.109	0.103	0.121	0.108
	(0.310)	(0.312)	(0.304)	(0.326)	(0.311)
N of Children age 5-10	0.177	0.175	0.185	0.161	0.160
	(0.382)	(0.381)	(0.388)	(0.368)	(0.367)
N of Children age 11-15	0.208	0.175	0.200	0.174	0.167

	(0.406)	(0.381)	(0.400)	(0.379)	(0.373)
Hh income band 1	0.102	0.117	0.105	0.0824	0.159
	(0.302)	(0.322)	(0.307)	(0.275)	(0.366)
Hh income band 2	0.0100	0.00812	0.0118	0.0250	0.00421
	(0.0997)	(0.0898)	(0.108)	(0.156)	(0.0648)
Hh income band 3	0.0314	0.0414	0.0391	0.0387	0.00843
	(0.174)	(0.199)	(0.194)	(0.193)	(0.0915)
Hh income band 4	0.0866	0.0609	0.0651	0.0524	0.0239
	(0.281)	(0.239)	(0.247)	(0.223)	(0.153)
Hh income band 5	0.0853	0.0682	0.0734	0.0762	0.0337
	(0.280)	(0.252)	(0.261)	(0.265)	(0.181)
Hh income band 6	0.128	0.106	0.0828	0.0861	0.104
	(0.334)	(0.308)	(0.276)	(0.281)	(0.305)
Hh income band 7	0.0828	0.0959	0.109	0.104	0.0801
	(0.276)	(0.295)	(0.312)	(0.305)	(0.272)
Hh income band 8	0.120	0.145	0.133	0.140	0.107
	(0.326)	(0.352)	(0.339)	(0.347)	(0.309)
Hh income band 9	0.139	0.149	0.157	0.162	0.162
	(0.346)	(0.357)	(0.364)	(0.369)	(0.368)
Hh income band 10	0.115	0.124	0.124	0.137	0.190
	(0.320)	(0.330)	(0.330)	(0.344)	(0.392)
Hh income band 11	0.0991	0.0837	0.0994	0.0961	0.129
	(0.299)	(0.277)	(0.299)	(0.295)	(0.336)
White	0.875	0.891	0.867	0.878	0.862
	(0.331)	(0.312)	(0.339)	(0.328)	(0.345)
SOC missing	0.507	0.54	0.491	0.495	0.044
	(0.500)	(0.499)	(0.500)	(0.500)	(0.206)
SOC 11	0.017	0.017	0.03	0.017	0.069
	(0.128)	(0.128)	(0.171)	(0.130)	(0.253)
SOC 12	0.012	0.012	0.013	0.014	0.025
	(0.110)	(0.107)	(0.113)	(0.117)	(0.157)
SOC 13	0.002	0.008	0.001	0.001	0.018
	(0.047)	(0.089)	(0.033)	(0.034)	(0.132)
SOC 21	0.046	0.035	0.025	0.03	0.091
	(0.209)	(0.185)	(0.156)	(0.170)	(0.288)
SOC 22	0.028	0.027	0.031	0.03	0.043
	(0.165)	(0.161)	(0.174)	(0.170)	(0.203)
SOC 23	0.04	0.043	0.038	0.043	0.07
	(0.196)	(0.202)	(0.191)	(0.202)	(0.255)
SOC 24	0.03	0.025	0.026	0.033	0.061
	(0.171)	(0.157)	(0.159)	(0.180)	(0.239)
SOC 25	0.021	0.019	0.017	0.024	0.036
	(0.144)	(0.136)	(0.130)	(0.154)	(0.185)
SOC 31	0.006	0.009	0.011	0.006	0.023
	(0.074)	(0.093)	(0.103)	(0.076)	(0.150)
SOC 32	0.01	0.014	0.009	0.008	0.025
	(0.100)	(0.116)	(0.093)	(0.089)	(0.157)
SOC 33	0.007	0.004	0.008	0.015	0.005

	(0.081)	(0.060)	(0.087)	(0.121)	(0.071)
SOC 34	0.012	0.013	0.011	0.008	0.019
	(0.110)	(0.113)	(0.103)	(0.089)	(0.137)
SOC 35	0.014	0.015	0.016	0.014	0.038
	(0.119)	(0.122)	(0.126)	(0.117)	(0.192)
SOC 36	0.021	0.022	0.016	0.022	0.052
	(0.144)	(0.146)	(0.126)	(0.146)	(0.222)
SOC 41	0.036	0.025	0.033	0.039	0.071
	(0.185)	(0.155)	(0.180)	(0.194)	(0.257)
SOC 42	0.018	0.019	0.014	0.02	0.041
	(0.132)	(0.136)	(0.118)	(0.139)	(0.198)
SOC 51	0.002	0.009	0.008	0.007	0.006
	(0.047)	(0.093)	(0.087)	(0.083)	(0.080)
SOC 52	0.006	0.01	0.014	0.007	0.022
	(0.074)	(0.100)	(0.118)	(0.083)	(0.145)
SOC 53	0.008	0.007	0.015	0.009	0.008
	(0.088)	(0.085)	(0.122)	(0.096)	(0.087)
SOC 54	0.004	0.006	0.012	0.008	0.014
	(0.067)	(0.076)	(0.108)	(0.089)	(0.117)
SOC 61	0.037	0.026	0.04	0.03	0.053
	(0.188)	(0.159)	(0.196)	(0.170)	(0.225)
SOC 62	0.012	0.012	0.01	0.01	0.013
	(0.110)	(0.110)	(0.098)	(0.101)	(0.112)
SOC 71	0.024	0.019	0.026	0.029	0.038
	(0.155)	(0.136)	(0.159)	(0.167)	(0.192)
SOC 72	0.013	0.009	0.017	0.025	0.017
	(0.115)	(0.096)	(0.130)	(0.157)	(0.128)
SOC 81	0	0.005	0.001	0.003	0.009
	(0.000)	(0.071)	(0.033)	(0.059)	(0.094)
SOC 82	0.014	0.014	0.016	0.012	0.03
	(0.119)	(0.119)	(0.126)	(0.107)	(0.172)
SOC 91	0.003	0.004	0.005	0.002	0.009
	(0.058)	(0.060)	(0.073)	(0.048)	(0.094)
SOC 92	0.026	0.02	0.027	0.015	0.032
	(0.158)	(0.141)	(0.162)	(0.121)	(0.175)
SOC 93	0.023	0.015	0.019	0.024	0.018
	(0.151)	(0.122)	(0.138)	(0.154)	(0.132)
N	899 (11.9%)	1,387 (18.4%)	927 (12.3%)	869 (11.5%)	787 (10.4%)

Notes: unweighted socio-demographic characteristics in OTUS data November 2022 – March 2025.

Table C2: Summary Statistics of time use in OTUS data across waves

	Waves								
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
Sleeping	505.83	493.56	487.96	488.77	490.72	497.85	495.91	494.09	484.4
	(87.00)	(76.03)	(76.42)	(82.25)	(86.26)	(84.30)	(90.04)	(92.60)	(89.94)
Personal care	115.23	118	112.43	118.61	116.5	119.45	119.14	121.54	119.99
	(58.35)	(58.47)	(54.00)	(69.72)	(64.80)	(65.51)	(62.42)	(61.75)	(62.68)
Total work	390.42	431.8	430.69	431.85	424.85	427.5	436.96	445.6	434.4
	(157.64)	(142.35)	(149.11)	(141.25)	(149.47)	(146.45)	(136.78)	(137.39)	(142.53)
Travelling	24.03	52.85	41.7	56.59	62.8	65.56	70.89	71.15	69.52
	(39.91)	(54.06)	(53.66)	(60.72)	(63.02)	(70.94)	(68.95)	(68.87)	(67.15)
Unpaid work	112.73	91.91	102.9	98.3	97.59	104.22	98.68	95.62	98.3
	(96.75)	(84.74)	(91.45)	(88.31)	(83.92)	(88.41)	(86.42)	(87.95)	(86.16)
Unpaid care	32.43	22.85	23.13	22.26	22.76	22.83	20.96	21.01	12.97
	(83.38)	(52.65)	(52.65)	(50.76)	(53.42)	(55.51)	(52.71)	(51.71)	(36.61)
Watching TV	121.94	114.42	123.84	107.32	110.37	97.77	98.64	98.56	95.55
	(94.56)	(83.33)	(86.25)	(90.33)	(89.67)	(83.85)	(87.45)	(86.84)	(86.96)
Leisure	61.62	49.57	46.11	52.65	56.61	43.84	43.77	36.94	42.73
	(79.41)	(72.82)	(64.45)	(79.86)	(81.92)	(74.16)	(78.57)	(66.07)	(73.87)
Fitness/wellbeing	21.57	18.25	17.59	16.11	13.16	16.34	14.66	14.12	16.95
	(37.34)	(38.71)	(34.01)	(33.07)	(31.08)	(35.59)	(34.18)	(33.49)	(37.18)
Social media/internet	48.82	42.87	50.11	43.31	41.51	40.47	37.07	35.6	34.09
	(69.91)	(62.25)	(69.24)	(63.00)	(71.12)	(60.98)	(68.00)	(61.07)	(59.66)
N									

Notes: unweighted number of minutes in work and other main activities. Standard deviations in parentheses.

Table C3: Comparison of main summary between statistics Annual Population Survey and OTUS data

	APS			OTUS waves				
	2019	**2022**	**2024**	**5**	**6**	**7**	**8**	**9**
Age: less than 34	0.344	0.341	0.334	0.336	0.315	0.318	0.315	0.322
	(0.475)	(0.474)	(0.472)	(0.473)	(0.465)	(0.466)	(0.465)	(0.467)
Age: 35 to 44	0.224	0.231	0.232	0.227	0.240	0.243	0.239	0.251
	(0.417)	(0.422)	(0.422)	(0.419)	(0.427)	(0.429)	(0.427)	(0.434)
Age: 45 to 55	0.261	0.250	0.250	0.213	0.221	0.225	0.233	0.206
	(0.439)	(0.433)	(0.433)	(0.410)	(0.415)	(0.418)	(0.423)	(0.405)
Age: 55+	0.171	0.178	0.184	0.224	0.224	0.214	0.213	0.221
	(0.376)	(0.382)	(0.387)	(0.417)	(0.417)	(0.410)	(0.410)	(0.415)
Female	0.474	0.478	0.479	0.455	0.462	0.458	0.470	0.468
	(0.499)	(0.500)	(0.500)	(0.498)	(0.499)	(0.498)	(0.499)	(0.499)
Single	0.323	0.329	0.322	0.490	0.481	0.471	0.457	0.501
	(0.468)	(0.470)	(0.467)	(0.500)	(0.500)	(0.499)	(0.498)	(0.500)
Higher education	0.456	0.483	0.517	0.537	0.524	0.483	0.467	0.513
	(0.498)	(0.500)	(0.500)	(0.499)	(0.500)	(0.500)	(0.499)	(0.500)
N	122,019	81,158	49,862	899	1,387	927	869	787
	(48.2%)	(32.1%)	(19.7%)	(18.5%)	(28.5%)	(19.0%)	(17.8%)	(16.2%)

Notes: weighted socio-demographic characteristics in APS and OTUS data November 2022 – March 2025. APS and OTUS survey weights used for both surveys.

Table C4: Summary Statistics of primary time use in waves 5 to 9 by place of work, gender and higher education (full sample)

	Men		Women	
	Working from the workplace	Working from home	Working from the workplace	Working from home
Sleeping	482.027	516.313	494.654	506.357
	(88.861)	(88.039)	(94.993)	(83.773)
Personal care	112.987	109.238	123.431	109.585
	(58.732)	(55.404)	(62.653)	(58.219)
Total work	487.559	455.997	453.441	453.524
	(107.182)	(89.753)	(108.501)	(109.920)
Travelling	85.461	30.202	76.901	31.171
	(67.651)	(46.521)	(60.786)	(45.056)
Unpaid work	67.141	89.272	93.693	111.009
	(64.370)	(71.493)	(75.403)	(80.242)
Unpaid care	14.823	22.642	16.188	22.979
	(38.575)	(54.294)	(43.829)	(53.365)
Watching TV	96.899	92.634	86.845	95.386
	(85.971)	(81.747)	(82.371)	(82.469)
Leisure	45.097	51.698	37.789	41.455
	(80.293)	(80.064)	(67.803)	(67.029)
Fitness/wellbeing	11.001	24.156	10.548	19.912
	(29.084)	(41.373)	(27.255)	(36.362)
Social media/internet	28.134	37.252	35.861	38.861
	(49.435)	(61.364)	(57.481)	(63.282)
Missing	83.838	79.522	75.905	67.041
	(94.367)	(80.694)	(86.098)	(59.134)
N	1,489 68.0%	700 32.0%	1,512 68.8%	685 31.2%

Notes: weighted mean number of minutes in work and other main activities. Standard deviations in parentheses.

Table C5: Summary statistics of primary time use in waves 5 to 9 by place of work, gender and higher education (graduates)

	Men		Women	
	Working from the workplace	Working from home	Working from the workplace	Working from home
Sleeping	472.947	506.482	481.503	507.324
	(84.523)	(82.105)	(78.713)	(81.161)
Personal care	113.741	109.919	119.361	108.571
	(57.242)	(56.593)	(56.588)	(52.643)
Total work	480.309	463.125	463.478	447.527
	(109.571)	(94.747)	(106.134)	(100.368)
Travelling	94.866	28.468	85.831	31.386
	(71.766)	(44.245)	(61.719)	(44.955)
Unpaid work	68.340	93.569	86.586	111.962
	(62.810)	(73.811)	(68.909)	(77.084)
Unpaid care	19.550	27.238	20.205	26.183
	(46.148)	(58.062)	(47.927)	(55.251)
Watching TV	90.113	93.306	86.010	92.537
	(81.313)	(80.814)	(79.347)	(78.183)
Leisure	46.470	47.863	40.985	41.066
	(77.424)	(73.941)	(63.498)	(67.153)
Fitness/wellbeing	12.841	23.185	12.020	23.006
	(29.628)	(39.994)	(27.639)	(38.979)
Social media/internet	34.135	38.548	37.647	42.281
	(55.496)	(61.650)	(57.852)	(62.444)
Missing	76.220	71.071	69.921	76.333
	(77.820)	(67.963)	(87.734)	(67.927)
N	711	496	782	469
	58.9%	41.1%	62.5%	37.5%

Notes: weighted mean number of minutes in work and other main activities. Standard deviations in parentheses.

Table C6: Summary statistics of secondary time use (whilst working) in waves 5 to 9 by place of work (full sample)

	Men		Women	
	Working from the workplace	Working from home	Working from the workplace	Working from home
Sleeping & Personal care	10.84	12.98	10.09	12.87
	(31.06)	(32.41)	(28.97)	(35.82)
Travel	0.93	0.2	0.49	0.71
	(10.26)	(3.56)	(3.96)	(6.59)
Unpaid work & Unpaid care	2.33	5.39	3.11	7.37
	(25.38)	(28.34)	(25.81)	(26.97)
Watching TV & Leisure & wellbeing/fitness	15.83	34.53	13.03	31.1
	(72.6)	(97.09)	(55.66)	(97.92)
Social media/Internet browsing	12.69	13.9	10.91	10.24
	(58.7)	(53.53)	(53.17)	(38.13)
N	1,489 68.0%	700 32.0%	1,512 68.8%	685 31.2%

Notes: weighted mean number of minutes in secondary activities while the main activity is paid work. Standard deviations in parentheses.

Table C7: Summary Statistics of secondary time use (whilst working) in waves 5 to 9 by place of work (graduates)

	Men		Women	
	Working from the workplace	Working from home	Working from the workplace	Working from home
Sleeping & Personal care	11.099	12.191	11.121	14.899
	(30.246)	(30.678)	(26.383)	(42.397)
Travel	1.153	0.181	0.699	0.344
	(10.234)	(2.705)	(5.136)	(4.166)
Unpaid work & Unpaid care	3.448	5.005	3.451	7.597
	(34.305)	(28.842)	(28.813)	(31.116)
Watching TV & Leisure & wellbeing/fitness	15.137	35.543	11.537	30.164
	(67.786)	(94.080)	(49.306)	(95.354)
Social media/Internet browsing	11.265	15.557	11.633	13.550
	(46.101)	(57.872)	(54.912)	(46.112)
N	1,489 68.0%	700 32.0%	1,512 68.8%	685 31.2%

Notes: weighted mean number of minutes in secondary activities while the main activity is paid work. Standard deviations in parentheses.

Table C8: Detailed Activities by Activity type - OTUS data

Activity number	Variable label	Activity type*
1	Sleeping	1
70	Resting (doing nothing) or in bed not asleep	1
2	Washing, dressing, using the bathroom, or self-grooming	2
3	Medication or other health-related care	2
4	Eating	2
7	Snacking	2
8	Drinking	2
9	Working	3
10	Working from home, café or other workspace (WAVE 1 ONLY)	4
11	Working from home	4
18	Travelling	5
106	Travelling to or from paid work (e.g. commuting, to attend a conference, to visit clients)	5
107	Travelling to or from unpaid work (e.g. caring for others, volunteering)	5
108	Travelling to or from a shop (e.g. supermarket, garden centres, takeaways)	5
109	Travelling to or from socialising with others outside a private home (e.g. restaurant, pub, park)	5
110	Travelling to escort children to or from childcare or school	5
111	Travelling to or from another place (e.g. holiday, visiting family or friends, escorting others, medical centre, dentist, gym, appointments or errands)	5
5	Making food and drinks, cooking or washing up	6
6	Making food and drinks, cooking	6
19	Cleaning, hoovering, tidying house, sorting the bins	6
20	Using a dishwasher or washing up	6
21	Ironing, washing, other laundry tasks or mending clothes	6
22	Repairing, maintaining or making household goods, or vehicles	6
23	Caring for or playing with pets (including walking the dog)	6
24	Caring for or playing with pets	6
25	Walking the dog	6
26	Packing or unpacking, preparing for journey	6
27	Arranging, sorting or unpacking household items (e.g. unpacking shopping, organising and clearing out storage or rooms)	6
28	Lighting fire or cleaning fireplace, log burner or wood burning stove	6
29	DIY or gardening	6
30	Volunteering as part of a group, organisation, charity or sports club	6
46	Buying something, shopping	6
47	Browsing things to buy later	6
48	Window shopping	6
49	Browsing things to buy later, window shopping	6
50	Queueing or waiting	6
51	Banking, household errands, appointments including GP and dentist	6
52	Financial tasks (e.g. banking), sorting out bills, household errands, appointments (including doctors, dentist or similar)	6

53	Completing a document (e.g. job or university application, passport or benefit form or similar)	6
54	Household administration tasks (e.g. banking, sorting out bills)	6
55	Attending appointments or errands (e.g. doctor, vet, bank, hospital, haircut, beautician, garage, etc)	6
112	DIY	6
113	Gardening	6
31	Feeding, washing, dressing or preparing meals for children	7
32	Supporting, comforting or cuddling children	7
33	Reading, playing with, or helping children with homework	7
34	Reading to children	7
35	Playing with children	7
36	Helping children with homework (including home-schooling)	7
37	Reading with children, helping with homework, doing other educational activities with children	7
38	Homeschooling children	7
39	Attending or watching a child's event or activity	7
40	Teaching children life skills (including potty training, dressing, or tying shoelaces)	7
41	Teaching children to develop, including writing, counting, role-play, cooking and baking	7
42	Time with child in your care (secondary activity)	7
43	Other childcare not elsewhere listed	7
44	Time with an adult in your care (secondary activity)	7
45	Helping, caring or looking after adults	7
56	Watching TV, Blu-ray or DVDs	8
57	Streaming TV or videos on the internet for entertainment (e.g. Netflix, Now TV or YouTube)	8
58	Watching TV and DVDs (including streaming, e.g., Sky, Netflix, Amazon prime, Disney+, YouTube etc)	8
59	On a work break (e.g. lunch)	9
60	Listening to music, podcasts, audiobooks, talk shows, radio or news	9
64	Reading books, magazines or newspapers	9
65	Socialising, spending time with friends, family, neighbours and colleagues	9
67	Playing games or computer gaming	9
68	Visits to cinema, theatre, concerts, sporting events, museums, galleries, library etc	9
69	Hobbies and other leisure activities	9
77	Taking other form of leisure time	9
78	Gym, fitness or exercise classes	10
79	Running or jogging	10
80	Playing team sports	10
81	Playing other sports and exercising	10
82	Going for a walk as exercise	10
83	Cycling	10
84	Meditating, having a massage, spa or well-being treatments	10
85	Other health or well-being activity	10
61	Browsing internet	11
62	Checking email	11

63	Checking or using social media	11
66	Telephoning (or video calling), emailing, texting or writing letters	11
75	Checking phone or tablet	11
91	Writing online public blogs or reviews	11
92	Writing open-source software for public	11
93	Creating or coding a website	11
94	Writing online or creating content for public	11
95	Assisting others online e.g. on a forum	11
96	Supporting a cause on social media or petition website	11
98	Finding guidance on internet e.g. on YouTube or websites	11
100	On computer (no main purpose)	11
101	Using a computer or laptop, going online	11
102	Other computer or laptop use (e.g. creating or coding a website, writing online or creating content for public, assisting others online)	11
71	Just talking with spouse, children or parents, family, friends or neighbours	12
72	Attending religious event or meeting	12
73	Attending a political meeting	12
74	Attending a meeting or an event	12
76	Having a conversation	12
86	Attending formal education, lectures, classes, university (not for leisure)	12
87	Attending formal education or taking a course	12
88	Taking a course for fun	12
89	Studying, revising or doing homework	12
90	Learning or teaching yourself a skill not involving taught classes	12
97	Using a device for directions	12
99	Using a computer for other purposes (not elsewhere listed)	12
103	Praying	12
104	Smoking or vaping	12
105	Completing the time-use diary	12
114	Having a conversation (include telephone and video calling)	12
115	Writing, texting or emailing	12
199	Other activities not listed (if private time then please write 'personal')	12
12	Working from a café or other workspace	12
13	Providing childcare, cleaning or doing odd jobs for pay	12
14	Leasing or renting things you own (excluding business)	12
15	Using your private vehicle to earn money, including delivery services	12
16	Showing your own house, flat or building to potential buyers	12
17	Selling your things, apart from your home	12

* Activity types: 1 Sleep/rest; 2 Personal care; 3 Working away from home; 4 Working from home; 5 Travelling; 6 Unpaid household work; 7 Unpaid care; 8 Watching TV; 9 Leisure; 10 Exercise/sports/well-being; 11 Social Media/Internet; 12 Other.

Appendix D: Regression Results

Table D1a: Time across different activities (November 2022-March 2025) – Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Sleeping	Personal care	Travel	Unpaid work	Unpaid care	Watching TV	Leisure	Well-being	Social media/ Internet	Tot work
	All 2022-2025									
Constant	490.875***	154.246***	67.355***	96.297***	-11.735*	111.134***	26.268*	6.524	52.569***	447.902***
	(18.472)	(12.648)	(12.622)	(15.023)	(6.738)	(17.335)	(15.868)	(7.019)	(15.015)	(21.314)
Female	5.447	11.418***	-7.613***	23.076***	2.778*	-12.143***	-13.513***	-1.573	6.290**	-16.258***
	(4.490)	(2.796)	(2.839)	(3.157)	(1.599)	(4.034)	(3.929)	(1.390)	(2.598)	(4.707)
WFH	36.364***	-2.606	-65.596***	25.662***	6.895***	-0.554	1.656	10.812***	6.119*	-20.879***
	(5.275)	(3.193)	(3.143)	(3.973)	(2.139)	(4.640)	(4.907)	(2.263)	(3.351)	(5.266)
WFH*Female	-16.355**	-9.503**	10.727***	-2.718	0.419	9.765	2.274	-2.398	-3.500	15.423*
	(7.146)	(4.503)	(3.975)	(5.608)	(3.110)	(6.330)	(6.152)	(2.737)	(4.636)	(8.090)
WFH+WFH*Female	20.01***	-12.11***	-54.87***	22.94***	7.315***	9.211**	3.930	8.414***	2.619	-5.456
	(5.328)	(3.359)	(2.913)	(4.219)	(2.262)	(4.527)	(4.061)	(1.736)	(3.558)	(6.961)
N	4,386	4,386	4,386	4,386	4,386	4,386	4,386	4,386	4,386	4,386
R^2	0.094	0.049	0.186	0.102	0.308	0.088	0.046	0.051	0.047	0.143

Notes: the table reports the estimates from a set of OLS regressions where the dependent variable is number of minutes spent in different groups of activities and the unit of observation is diaries. Regressions include a comprehensive set of demographic and socio-economic characteristics of the respondents, occupation and region dummies and they were estimated using survey weights. Robust standard errors in parenthesis. OTUS data from November 2022 to March 2025 (wave 5 to 9).

Table D1b: Time across different activities (November 2022-March 2025) - Graduates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Sleeping	Personal care	Travel	Unpaid work	Unpaid care	Watching TV	Leisure	Well-being	Social media/ Internet	Tot work
					Graduates 2022-2025					
Constant	474.557***	135.005***	70.930***	101.531***	-1.097	93.407***	49.064**	3.074	48.351***	439.486***
	(16.961)	(13.510)	(17.889)	(16.835)	(8.412)	(18.415)	(19.358)	(8.251)	(17.056)	(26.105)
Female	3.036	11.203***	-7.408*	14.635***	3.814*	-11.050**	-11.028**	-1.467	4.574	-7.351
	(4.337)	(3.590)	(4.182)	(3.958)	(2.045)	(5.287)	(5.590)	(2.108)	(3.866)	(6.418)
WFH	34.940***	-0.448	-71.987***	25.073***	9.670***	-0.556	-4.222	11.607***	2.913	-9.129
	(5.079)	(3.768)	(3.985)	(4.791)	(2.961)	(5.777)	(5.866)	(2.637)	(4.106)	(6.571)
WFH*Female	-7.658	-9.312*	10.986**	3.759	-1.970	9.011	3.651	-0.819	2.336	-5.725
	(6.626)	(5.261)	(5.173)	(6.556)	(3.911)	(7.730)	(7.624)	(3.420)	(6.132)	(8.809)
WFH+WFH*Fem	27.28***	-9.760***	-61***	28.83***	7.699***	8.455***	-0.571	10.79***	5.250	-14.85***
	(4.793)	(3.782)	(3.937)	(4.741)	(2.566)	(5.528)	(5.196)	(2.286)	(4.855)	(6.484)
N	2,458	2,458	2,458	2,458	2,458	2,458	2,458	2,458	2,458	2,458
R^2	0.109	0.059	0.256	0.128	0.349	0.083	0.077	0.062	0.063	0.188

Notes: the table reports the estimates from a set of OLS regressions where the dependent variable is number of minutes spent in different groups of activities and the unit of observation is diaries. Regressions include a comprehensive set of socio-demographic and economic characteristics of the respondents and they were estimated using diary weights. Robust standard errors in parenthesis. OTUS data from November 2022 to March 2025 (wave 5 to 9).

Table D2: Time in secondary activity while at work 2022-2025

	(1) Secondary Sleeping+ Personal care	(2) Secondary Travel	(3) Secondary Unpaid work+ Unpaid care	(4) Secondary Watching TV+Leisure+ wellbeing/fitness	(5) Social media/Internet browsing
	Waves 5-9	Waves 5-9	Waves 5-9	Waves 5-9	Waves 5-9
			All		
Constant	4.992	3.883	-4.148	-11.897	-10.293
	(5.542)	(2.630)	(6.532)	(11.507)	(7.904)
Female	-0.041	-0.520	1.145	-1.641	-4.401
	(1.407)	(0.353)	(1.196)	(3.066)	(2.985)
WFH	1.159	-0.959**	3.210*	19.915***	1.140
	(1.899)	(0.381)	(1.641)	(4.850)	(2.915)
WFH*Female	0.365	1.122**	0.677	-2.630	-1.194
	(2.508)	(0.513)	(2.058)	(6.893)	(3.977)
WFH +WFH*Female	1.524	0.163	3.888***	17.28***	-0.0535
	(1.705)	(0.374)	(1.344)	(4.845)	(2.471)
N	4,386	4,386	4,386	4,386	4,386
R^2	0.018	0.016	0.022	0.034	0.017
			Graduates		
Constant	-0.658	6.537	-15.417	0.181	-4.883
	(6.598)	(4.503)	(9.591)	(12.641)	(10.382)
Female	0.075	-0.358	0.592	0.178	-1.571
	(1.808)	(0.468)	(2.526)	(4.158)	(3.091)
WFH	1.222	-1.086**	2.980	22.491***	3.302
	(1.979)	(0.491)	(2.543)	(5.926)	(3.500)
WFH*Female	2.760	0.659	1.338	-5.880	-1.799
	(3.140)	(0.598)	(3.176)	(8.400)	(4.911)
WFH +WFH*Female	3.982	-0.427	4.318***	16.61***	1.503
	(2.414)	(0.378)	(1.988)	(5.781)	(3.411)
N	2,458	2,458	2,458	2,458	2,458
R^2	0.016	0.019	0.024	0.035	0.019

Notes: the table reports the estimates from a set of OLS regressions where the dependent variable is number of minutes spent in different groups of secondary activities while the main activity is paid work, and the unit of observation is diaries. Regressions include a comprehensive set of socio-demographic and economic characteristics of the respondents and they were estimated using diary weights. Robust standard errors in parenthesis. OTUS data from November 2022 to March 2025 (wave 5 to 9).

Appendix E: Robustness checks

Table E1: Time across different activities (November 2022-March 2025) – Sample with no missing occupation information

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Sleeping	Personal care	Travel	Unpaid work	Unpaid care	Watching TV	Leisure	Well-being	Social media/ Internet	Tot work
	All 2022-2025									
Female	3.495	7.427**	-6.826*	26.676***	1.590	-9.330*	-18.599***	-0.342	8.603**	-17.363***
	(6.249)	(3.628)	(3.531)	(3.972)	(2.152)	(5.052)	(4.779)	(1.868)	(3.342)	(6.394)
WFH	27.438***	-10.321**	-68.706***	37.576***	7.221**	4.080	-5.048	10.459***	4.150	-11.951
	(7.529)	(4.775)	(4.358)	(5.714)	(3.066)	(6.241)	(6.832)	(3.116)	(4.733)	(7.617)
WFH*Female	-7.321	0.976	11.219**	-20.389***	-2.531	2.745	15.699*	-3.289	-4.488	15.131
	(10.013)	(6.410)	(5.385)	(7.551)	(4.003)	(8.443)	(8.311)	(3.817)	(6.268)	(11.662)
WFH+WFH*Female	20.12**	-9.345*	-57.49***	17.19***	4.690*	6.824	10.65**	7.170***	-0.339	3.180
	(7.871)	(4.787)	(4.186)	(5.323)	(2.566)	(6.233)	(5.310)	(2.426)	(4.838)	(10.650)
N	2,506	2,506	2,506	2,506	2,506	2,506	2,506	2,506	2,506	2,506
R^2	0.136	0.083	0.221	0.152	0.277	0.138	0.092	0.073	0.104	0.180

Notes: the table reports the estimates from a set of OLS regressions where the dependent variable is number of minutes spent in different groups of activities and the unit of observation is diaries. Regressions include a comprehensive set of demographic and socio-economic characteristics of the respondents, occupation and region dummies and they were estimated using survey weights. Robust standard errors in parenthesis. Sample does not include respondents with missing SOC code for their occupation. OTUS data from November 2022 to March 2025 (wave 5 t