Trends in Effort at Work in the UK

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Abstract

This paper links detailed 24-hour diary surveys in the United Kingdom (UK) for the last four decades, to provide evidence of an increase in work effort in three specific dimensions: timing, nature, and composition. We rule out certain proposed explanations of these trends, finding that the decrease in the frequency of on-the-job leisure is more pronounced for workers in routine task-intensive occupations. Alternative supply-side and demand-side explanations, such as changes in relative preferences for leisure, or an increase in off-shoring, or competition for jobs, cannot explain our results. Our findings suggest that the amount and frequency of on-the-job leisure can be used as a measure of work effort, and that the routine-biased technological changes experienced during this period lie at the root of the increase in work effort in the UK.

JEL: J22, J23, J24

1. Introduction

In recent decades, labour markets have witnessed an unprecedented polarization of employment, as workers in middle-wage occupations experienced a decrease in their share of overall employment, particularly in the US during the 1980s and 1990s (Autor, et al., 2006; 2008; Acemoglu and Autor, 2011; Autor and Dorn, 2013) and in Europe (Goos and Manning, 2007; Goos et al., 2009; 2014). One reason for the disappearance of many middle-wage occupations has been technological change (e.g. automation of routine job tasks), which reduces the real cost of automating many of the routine tasks characteristic of these jobs, creating strong economic incentives for firms to substitute ever cheaper and more powerful computing power for relatively expensive human labour (Autor et al., 2003; Autor 2015;Acemoglu and Restrepo, 2019,2020). However, while the theoretical predictions and empirical implications of the effects of automation on aggregate employment, wages, inequality, and productivity are well understood, little is known about how automation and technological change affect the work process. This paper looks beyond the aggregate employment effects of technological change/automation to present new empirical evidence on the relationship between technological change and the structure of work, the latter serving as a measure of work effort.

Our proposed economic framework follows the recently developed task-content model for technological change/automation (Acemoglu and Restrepo, 2019, 2020). The economic principles of this framework predict that technological change/automation affects the composition of tasks for those workers who remain employed, reducing the relative contribution of workers to routine tasks – now performed by computers/robots – and increasing the relative contribution of workers to abstract tasks. Given the changing nature of the tasks towards abstraction, with a high degree of complementarity to the tasks done by robots and computers, this may represent a change in the structure of work, affecting the levels of work effort. Prior evidence has shown that technological change/automation leads to a more efficient allocation of job tasks, due to increased efficiency at all stages of the production process, by reducing unscheduled downtime and stoppage periods (Ichniowski et al., 1997), as well as by shortening setup times, run times, and inspection times (Bartel et al., 2007). Furthermore, technological change/automation changes the content of the tasks performed by workers in traditionally routine, task-

intensive occupations, and creates many new tasks (e.g. programming, design, maintenance of high-tech equipment, such as software and app development, database design and analysis, and computer-security-related tasks) that are highly relevant to the functioning of robots/machines.[1] Thus, workers in routine task-intensive occupations may have experienced larger changes in the structure of their work, ending up with a work process characterized by a distribution of work effort that more closely resembles the work process of workers in non-routine, task-intensive occupations.

We collect six UK time-use surveys from the mid-1980s to the late 2010s, containing detailed activity reported during 24-hour periods, and construct two measures of work effort. Despite that total hours of work have been used to measure work effort, normal weekly hours of work can only be a crude proxy for hours actually worked and may miss important information on what workers do while on the job (Hamermesh, 1990). Dickinson (1999) extends the traditional model of work-leisure choice to explicitly consider the consumption of on-the-job leisure, in order to get a better picture of hours of work. Following this line of research, we define the consumption of on-the-job leisure as time spent in non-work-related activities while at work (see Hamermesh, 1990; Giménez-Nadal et al., 2018; Burda et al. 2020). First, we measure the consumption of on-the-job leisure. Second, we measure the frequency of on-the-job leisure, since the sequence information in the diary provides a clear picture of the distribution of effort throughout the work process.

We first demonstrate an increase in the work effort of workers in the UK, as we observe a decrease in both the amount and frequency of on-the-job leisure. This is consistent with the strand of literature analysing the intensification of work in the UK in recent decades (Green, 2001; Green and McIntosh, 2001; Green, 2004; Green et al. 2022). Second, we observe that workers in routine task-intensive occupations experience larger changes in the structure of job tasks, that is, experience greater increases in work effort, measured as the frequency of on-the-job leisure, in comparison to workers in abstract task-intensive occupations. These results are consistent with the task-content model where technological change/automation produces changes in the structure of work, with larger increases for workers in routine task-intensive occupations.

[1] These examples correspond to relatively high-level IT skills. Other new tasks, not so specific with high-level IT skills, include activities such as emailing, and using spreadsheets and word-processing software.

We rule out competing supply-side and demand-side explanations for the decrease in the consumption and frequency of on-the-job leisure, and none of the alternative theories appear to account for the key aspects of the evidence presented. Furthermore, we use the 1986, 1992, 1997, 2001, 2006, 2012, and 2017 Skills and Employment Surveys (SES) from the UK, to link our measures of work effort to indicators of computer use at work, the presence of unions in the workplace, and the proportion of workers with permanent contracts, and our evidence supports the argument that the introduction of computerized and/or automated equipment has been driving the intensification of work effort in the UK.

This paper contributes to recent developments in the literature of routine-biased technological change by moving beyond employment effects and looking at how automation relates to work effort. Prior literature on automation technology and the organization of work processes focuses on the firm's production function and firm-level outcomes, and generally adopts a case-study analysis of one or more workplaces in narrowly defined industries. This literature holds that automation technology leads to a more efficient allocation of job tasks, leading in turn to greater efficiency at all stages of the production process, for example by reducing unscheduled downtime and stoppage periods (Ichniowski et al., 1997), as well as by shortening setup times, run times, and inspection times (Bartel et al. 2007). Furthermore, Green et al. (2022) explain that for more than half (51%) of work intensification in the UK, effort-biased technological change is among the explanatory factors. We use large, worker-level representative surveys to document increases in work effort, following the new and more specialized tasks resulting from technological change/automation.

The remainder of the paper is organized as follows. Section 1 describes the time diary data used in this paper, the conceptualization of work effort, and the evolution of work effort over time. Section 2 describes the data and the work effort indicators and shows the trends in work effort in the UK. Section 3 analyses supply-side and demand-side explanations underlying the observed trends in work effort. Section 4 concludes.

2. Work effort in UK Time Use Surveys

2.1. The data

We employ large-scale, representative time-diary surveys for the UK, where respondents record their activities for consecutive 24-hour periods. Specifically, we use surveys from 1983, 1987, 1995, 2000, 2005, and 2015, which provide a unique opportunity to examine how activities at work vary by occupation and other socio-economic characteristics over extended periods of time.[2] Such surveys have become the preferred method of gathering information on time spent on market work, non-market work, and leisure, in the same way that money expenditure diaries have become the gold standard in the consumption and expenditure literature (see Table A1 in Supplementary Appendix for a detailed description of the surveys used).

We follow the literature and restrict the sample to non-retired/non-student individuals between the ages of 21 and 65, inclusive (see Aguiar and Hurst, 2007; Gimenez-Nadal and Sevilla, 2012) who devote at least one hour to market work activities during the diary day, excluding commuting, and work full-time.

2.1.1. On-the-job leisure (consumption).

Work effort is traditionally measured as the number of hours of work, which is normally gathered from nationally representative labour force surveys that ask respondents about normal work hours per week, month, or year. However, normal weekly/monthly/yearly hours of work can only be a crude proxy for hours actually worked (Barrett and Hamermesh, 2019) and may miss important information regarding what workers do while on the job (Hamermesh, 1990). The concepts of 'extensive' and 'intensive' effort have been developed by Francis Green and colleagues to measure work effort. While 'extensive effort' refers to the number of hours in a day that individuals spend working, 'intensive effort' refers to the intensity of that work (Green, 2001). Recent analyses of the intensification of work in the UK have shown that technological change has played a major role in the observed trends (Green and McIntosh, 2001; Green, 2006; Green et al., 2022).

Given the limitation of hours of work as a measure of work effort, the labour supply literature has extended the traditional model of work-leisure choice to explicitly consider the consumption of on-the-job leisure, to obtain a more accurate picture of hours of work

[2] From the Multinational Time Use Study (MTUS) at https://www.timeuse.org/mtus.

(Dickinson, 1999). Following this approach, we define the consumption of on-the-job leisure as time spent in non-work-related activities while at work (Hamermesh, 1990; Gimenez-Nadal et al., 2018; Burda et al., 2020). [3] We follow Hamermesh (1990) and consider the consumption of on-the-job leisure for leisure-related and other non-work activities.[4]

2.1.2. The frequency of on-the-job leisure

The frequency of on-the-job leisure has not been previously analysed in the literature. We construct two indicators: the number of on-the-job leisure episodes and the amount of working time until consuming on-the-job leisure. A higher number of on-the-job leisure episodes indicates a greater frequency of on-the-job leisure, while a longer working time until consuming on-the-job leisure indicates a lower frequency of on-the-job leisure. This second indicator is calculated by dividing the total amount of time spent working by the number of work spells in the diary day.

Table 1 shows an example of a working day for a worker in the UK.[5] The diarist spent 8 hours and 40 minutes at work, starting at 8:00 am, when the first episode of paid work was recorded in the diary (after commuting), and finishing at 4:40 pm when the last episode of paid work was recorded in the diary. Of the 8 hours and 40 minutes that the respondent spent at work, 7 hours and 30 minutes were spent working. There were three work spells of 3 hours, 2 hours and 10 minutes, and 2 hours and 20 minutes. The first work spell began at 8:00 am and lasted until 11:00 am. From 11:00 am to 11:20 am, the respondent recorded having a snack, followed by relax/do nothing from 11:20 am to 12:00

[3] *While at work* is defined as the time from the moment the respondent first begins work until the moment in which the respondent records the last work episode of the diary day. Commuting episodes are not considered as market work time.

[4] We employ the term 'on-the-job leisure' in a broad sense, referring to activities different from paid work that are undertaken during the time the respondent is at work (i.e. time not spent working while on the job). See Table A2 in the Appendix for a description of the activities considered as 'on-the-job leisure'.

[5] In the current context, diaries are often left behind and individuals can answer them at their discretion in some cases, not necessarily during work breaks, while at other times interviewers ask respondents about their prior data, which may affect how individuals fill in the diary. Consequently, the timeframe to which the diary pertains can vary depending on the survey (see Table A3 in the Appendix). For example, some diary surveys refer to the same days, while others correspond to the previous day. We estimate OLS regressions controlling for three decade dummies (1990s, 2000s, and 2010s), socio-demographic characteristics, and the total number of activities reported by the individual in the diary day. Furthermore, we control for survey methodology, where we include dummy variables to distinguish between data collected through self-completion (1) or by interview (0), as well as whether the diary pertains to the same day of the interview (1) or the preceding day (0). The results are presented in Table A4 of the Appendix and are consistent with ur results.

pm. The respondent went back to work again at 12:00 pm, finishing this second work spell, for lunch, at 2:10 pm. The third work spell began at 2:20 pm and lasted until 4:40 pm.

The consumption of on-the-job leisure was 1 hour and 10 minutes in totalal (1.16 hours). Of this time, the respondent spent 40 minutes in leisure activities (relax/do nothing), while the remaining 30 minutes were spent in meals at work. As for the frequency of on-the-job leisure, there were two on-the-job leisure episodes during the 1 hour and 10 minutes of on-the-job leisure: a first episode between 11:00 and 12:00, with one passive leisure activity and a meal at work, and a second episode between 14:10 and 14:20. Similarly, the respondent worked for an average of two and a half hours before consuming on-the-job leisure, which was calculated by dividing the 7 hours and 30 minutes that the respondent was working by the three work spells recorded in the diary.[6]

2.2. Trends in work effort

Columns 1 to 4 in Table 2 show trends of the time spent at work, split between the time working and the time spent at leisure, and the frequency of on-the-job leisure. Columns 5 and 6 show the changes in the consumption and frequency of on-the-job leisure between the 1980s and the 2010s, and the p-values of the difference, respectively. To ensure a constant representation of types of individuals and days of the week, the demographic weighting used in Aguiar and Hurst (2007) and Gimenez-Nadal and Sevilla (2012) is employed. The demographic composition of workers is likely to differ over time, which could have implications for time-use patterns, including the consumption and frequency of on-the-job leisure.

2.2.1. Trends in working time

Table 2 shows that the amount of time spent working in the UK increased by one hour from the 1980s to the 1990s, from approximately 7 hours and 24 minutes per day, before returning to 1980s levels during the 2000s and 2010s. Our results for trends in work hours

[6] Figure 1 in the Appendix illustrates the percentage of workers in our sample who are either at work or at leisure for every hour of the diary day (see Table A5 in the Appendix for values). For instance, at 1 pm, 90% of full-time workers are present, with 51% working and 39% engaging in on-the-job leisure. Most of the on-the-job leisure activities are taken up by meals at work (see Table A6 in the Appendix).

are in line with prior analyses of survey data based on questions about weekly hours of work. Ohaian et al. (2008) documented an increase in work hours between the 1980s and 2000s in the UK, followed by a smooth decrease in work hours in the 2000s. Rogerson and Shimer (2011) showed a peak in the number of work hours around 1990.

2.2.2. Trends in on-the-job leisure

Against the backdrop of non-increasing working time, workers reduced the amount of time they spent in non-work activities while at work.[7] The consumption of on-the-job leisure declined by 15%, from approximately one hour and 22 minutes per working day at the beginning of the period to one hour and 10 minutes per working day by the end of the period. The frequency of on-the-job leisure also decreased over this period. The number of on-the-job leisure episodes decreased by around 22% in the UK, from 1.69 episodes per working day in the 1980s to 1.31 episodes at the end of the period. The time spent working before the consumption of on-the-job leisure also increased. Whereas in the 1980s, working time until consuming on-the-job leisure was around 3 hours and 19 minutes, by the end of the period workers had increased this measure by 17% (35 minutes).

3. Possible explanations for trends in work effort

3.1. Demand-side explanations

We analyse a range of factors that may help to explain the observed trends in work effort in the UK. These demand-side explanations include routine-biased technological change (RBTC), offshoring, and competition for jobs. Additionally, we discuss some other potential channels that we are unable to explain with the current data.

[7] Larger increases in work effort occur particularly during the first half of the period (i.e. between the 1980s and 1990s) coinciding with an intensification of routine-biased technological change. Overall, the trends in on-the-job leisure match the trends in technological changes. Stewart and Atkinson (2013) and Autor, (2015) document a peak of non-residential investments in Information Processing Equipment and Software up until the beginning of the 2000s. In particular, during the 1980s, investments in equipment, software, and structures for business grew by 2.7% per year on average, and by 5.2% per year between 1990 and 1999. Autor (2015) documents similar trends in the demand for information technology capital during the latter half of the 1990s. The falloff in information investment may explain the slowing growth of abstract task-intensive employment, since lower investment in IT dampens both innovative activity and the demand for high-skilled workers. Like any General Purpose Technology (GPT), IT technology experienced a key investment stage, during which demand for cognitive tasks complementary to capital investments increased, but once the new capital was in place there was a reduction in the number of workers performing cognitive tasks - those who were only needed to maintain the new capital. In the maturity stage, IT technology investment slows down, although the levels are higher than at the onset. These authors argue that the turn of the century is the approximate turning point for peak investment.

3.1.1. Routine-biased technological change

Prior literature on work has documented the polarization of employment because of routine-biased technological change in the UK, the US, and Europe. This has led to a decrease in the share of employment of middle-wage occupations, and the explanation commonly given for this phenomenon is the 'Routine-Biased Technological Change' (RBTC) framework proposed by Autor et al. (2003), predicting a displacement of workers engaged in routine, task-intensive occupations as new technologies substitute for traditional tasks. These workers belong to the group of middle-wage occupations.

The existing literature suggests that automation and technological change leads to a more efficient allocation of job tasks, resulting in greater efficiency at all stages of the production process (Ichniowski et al., 1997; Bartel et al., 2007). Additionally, these changes affect the types of tasks that workers in traditionally routine, task-intensive occupations are performing, by introducing many new tasks (e.g. programming, design, maintenance of high-tech equipment, software and app development, database design and analysis, and computer-security-related tasks). This has the potential to increase work effort. Thus, to investigate the relationship between automation and work effort, we analyse the composition of the changes in work effort, comparing the consumption and frequency of on-the-job leisure for workers in routine task-intensive and non-routine task-intensive occupations. Specifically, we examine whether the proportion of routine tasks for a given occupation is correlated with changes in work effort. (Autor, 2015; Acemoglu and Restrepo, 2020).

We link the diary information to a worker's occupation-specific Routine Task Intensity (RTI) index, originally developed by Autor and Dorn (2013) and Autor et al. (2015) and adapted by Goos et al. (2014) to the UK context.[8] In particular, Goos et al. (2014) report the RTI index for 21 two-digit ISCO88 occupational codes. We use the 1983, 2000, and 2015 UK TUS samples that have information on a worker's occupation.[9] Supplementary

[8] The RTI Index makes use of the O*NET program to collect data on occupations. However, the RTI employs a two-digit classification system of occupations, which may obscure many job-level distinctions. There are other task measures collected at the individual worker level, as demonstrated by DiNardo and Pischke (1997), Spitz-Oener (2006), Dustmann et al. (2009), Gathmann and Schönberg (2010), and others. Francis Green and colleagues have used indicators of workplace computing, automated equipment, and repetitive tasks obtained from the Skills and Employment Survey (SES) series to measure the degree of automation and ICT use in the workplace (Green et al., 2022).

[9] For our analysis, the 1995 and 2005 surveys cannot be used as they do not provide information on occupation. An in-depth description of the RTI index can be found in Appendix B. In Table B5 of the Appendix, we compare the three

Appendix B shows summary statistics of market-work time and on-the-job leisure indicators by occupation, according to their values on the RTI index. Workers in non-routine, task-intensive occupations spend comparatively more time working before consuming on-the-job leisure (see Table B5 in the Supplementary Appendix).

We estimate ordinary least squares (OLS) regression models for each measure of on-the-job leisure, as follows:

$$E_i = \mu + \beta_1 X_i + \beta_2 RTI_i + \beta_3 D_{t,i} + \beta_4 D_{t,i} * RTI_i + \varepsilon_i \qquad (1)$$

where E_i represents our measures of the consumption and frequency of on-the-job leisure for respondent *i*. The vector X_i includes person-specific, socio-demographic characteristics such as gender (ref. male), age, a dummy variable for secondary and university education (ref. primary education), a dummy variable for living in couple (ref. not in couple), the number of children under 18 in the household, and the total number of activities reported by the individual in the diary day.[10] We also control for hours worked during the diary day. Once hours of work are constant, we expect to see similar effects of RTI on the two frequency measures. Additionally, we control for the RTI index of the worker's occupation (β_2). β_3 is a vector of dummy variables for the years 2000 and 2015, to capture changes in the on-the-job leisure measures between the two surveys, and β_4 is the interaction between the vector of year dummies and the RTI index. ε_i is the error term. The coefficient of interest is β_4, which covers the interactions between the year dummies and the RTI index. The higher the values of the RTI index, the more routine-intensive an occupation is. Consequently, a greater magnitude in these coefficients indicates a larger decrease in work effort for workers in routine task-intensive occupations, compared to those in non-routine, task-intensive occupations during this period.

Table 3 displays the results of estimating Equation (1) on the consumption and frequency of on-the-job leisure, respectively. The coefficients on the 2000 and 2015 dummies in Table 3 indicate trends in the consumption of on-the-job leisure that are consistent with the results in Table 2. There is a decrease in the consumption and

measures of on-the-job leisure, as well as socio-demographic characteristics of workers. This table highlights some differences between the two samples, although one cannot assume that diaries with RTI information are inferior to diaries without RTI information.

[10] For the regression on the working time until on-the-job leisure, we exclude the hours of market work in the day, given the high correlation between the indicator and this variable. Results are consistent with the inclusion of this variable.

frequency of on-the-job leisure, given that the decade dummies are statistically significant at the 99% level. The decade dummies are negative in the case of the consumption of on-the-job leisure and the number of breaks for on-the-job leisure, and positive for time working before consuming on-the-job leisure.

The regression results in Table 3 suggest that the decline in on-the-job leisure is predominantly a period effect, but that for high-RTI occupations, on-the-job leisure spells are less frequent and thus more chunky. The coefficients on the interactions between the RTI index and the decade dummies show that there are important differences of this period effect across occupations, indicating that workers in routine task-intensive occupations decreased the frequency of on-the-job leisure to a greater extent than workers in non-routine task-intensive occupations.[11]

In the 1980s, routine task-intensive occupations had a higher frequency of on-the-job leisure than non-routine task-intensive occupations, although by the end of the period, differences across occupations had diminished, or even reversed, in terms of the frequency of on-the-job leisure. In particular, the coefficient on the RTI index indicates that at the beginning of the period, 'office clerks' (RTI=2.24), the occupation with the highest RTI index, had 0.71 more on-the-job leisure episodes and spent one hour and 39 fewer minutes at work before consuming on-the-job leisure than 'managers of small enterprises' (RTI=-1.52), the occupation with the lowest RTI index. During this period, the coefficients on the interaction of the 2000 and 2015 dummies with the RTI index, in Table 3, indicate that office clerks experienced a monotonic decrease in the frequency of on-the-job leisure, relative to managers.

In particular, the interaction coefficient between the 2015 dummy and the RTI index shows that office clerks experienced a decrease of 0.83 (3.76*0.22) more in the number of on-the-job leisure episodes than managers, and the time spent working before consuming on-the-job leisure increased by one hour and 39 minutes (3.76*0.44) compared to managers.[12] Thus, at the end of the period, office clerks were relatively worse

[11] One factor that may explain the increase in work effort as part of technological change is the monitoring of jobs. Technological change has allowed a reduction in the costs of monitoring jobs via computers, which can affect the effort of workers because greater monitoring reduces the chances of workers shying away from their tasks. However, we have found no statistical information on the level of monitoring of different occupations, and we cannot explore what part of the observed trends in work effort is due to greater monitoring.

[12] The difference in the RTI index values for 'office clerks' and 'managers of small enterprises' is 3.76 [2.24 - (-1.52)]. Multiplying this figure by the RTI index coefficient in Table 3 yields a difference at the beginning of the period between workers in the two occupations of 0.71 (3.76*0.19) in the number of on-the-job leisure episodes and of one hour and

off than managers, as they had 0.12 fewer on-the-job leisure episodes, and worked the same amount of time before consuming on-the-job leisure.

Overall, our results show that the decreases in the frequency of on-the-job leisure were comparatively larger for workers in routine task-intensive occupations, with higher values of the RTI index. These results support the notion that technological change may underlie the observed trends in work effort in the UK. Equation (1) resembles a difference-in-differences model, in which the primary focus of analysis centers on the systematic bias stemming from technological changes.

3.1.2. Competition for jobs, offshoring of jobs and labour market conditions

We alternatively test whether it is the mere threat of losing the job (because of automation) that affects on-the-job leisure. To test this hypothesis, we use the occupational change in employment for each occupation, computed as the percentage change in the share of employment that each occupation represents in comparison to the reference year (1985), and estimate Equation (1), adding the change in employment and its interaction with the RTI measure. Table 4 shows that the interaction terms between the RTI and the change in employment are not statistically significant for the consumption or frequency of on-the-job leisure, indicating that this channel is not behind the observed trends in work effort.

Prior literature has argued that offshoring of jobs could also explain employment losses for middle-wage occupations, since their job tasks are outsourced to workers in countries with lower labour costs (Acemoglu and Autor, 2011; Goos et al., 2014).[13] The fear that their work will be outsourced to other places with lower labour costs can make workers increase their effort in order to increase their productivity, and thus avoid such outsourcing. In those jobs that are more likely to be outsourced, we should expect to find larger increases in work effort, in comparison to jobs at lower risk of being outsourced. We analyse trends in the consumption and frequency of on-the-job leisure, using an occupation-specific offshoring index (BK index) obtained from Blinder and Krueger

39 minutes (3.76*0.44=1.65 hours per day) in the time working before consuming on-the-job leisure. Similarly, given the coefficient on the interaction between the 2015 dummy and the RTI index in Table 3, the relative decrease in the consumption and frequency of on-the-job leisure for office clerks, with respect to managers, is calculated as follows: 0.83 (3.76*0.22) fewer on-the-job leisure episodes and one hour and 39 more minutes (3.76*0.44=1.65 hours per day) of working before consuming on-the-job leisure.

[13] See Hummels et al. (2018) for a review of the effects of offshoring on labor markets.

(2013) and adapted to the ISCO-88 occupational classification by Goos et al. (2014). Higher values of the offshoring index indicate a higher probability of being offshored (see Suplementary Appendix B for a description of the values of the offshoring index for all occupations). We estimate Equation (1) but using the BK index instead of the RTI index.[14] Table A8 in Supplementary Appendix shows that offshoring cannot explain the observed trends.

An alternative explanation is related to local labour market conditions and the business cycle, both of which, generally, exert effects on the incentives to engage in non-work at work (Burda et al., 2020). Lazear et al. (2013) show that lower worker bargaining power, as a result of the recent financial crisis in the US, resulted in increases in work effort (measured as output per hour on the job) of those who remained employed. This may represent cyclical tolerance of the employer (labour hoarding) or local unemployment (efficiency wages). One way to analyse this factor would be to control for labour market slack using detailed local information and pooling the data. Some of the surveys used here do not contain detailed information on the location of the worker, and thus we cannot explore this channel.

3.2. Supply-side explanations

We now rule out supply-side explanations related to worker characteristics that may have led to the observed changes in the consumption and frequency of on-the-job leisure. In doing so, we consider education and the presence of children as possible driving forces of the observed patterns in work effort. Furthermore, we explore the composition of leisure outside the workplace to see if the observed trends in on-the-job leisure contrast with the trends in out-of-job leisure, and whether they may be related to changing preferences.

3.2.1. The role of education of workers

[14] We examine a more comprehensive model that contains interactions between possible confounding factors (e.g., education, presence of children, the Offshoring index) and dummy variables for time decades, based on Goos et al. (2015). We find that the RTI index and its related time interactions are statistically significant and demonstrate the expected behavior, whereas the other interaction terms do not (as seen in Table A7 of the Appendix). For the purpose of simplification, we utilize the results of Equation (1).

We explore whether the decreases in the consumption and frequency of on-the-job leisure stem from changes in the educational level of workers. Aguiar and Hurst (2007) and Gimenez-Nadal and Sevilla (2012) show increases in leisure time across industrialized countries, particularly for the least educated. Increases in leisure on the part of less educated workers, who tend to work in middle-wage occupations, are consistent with those workers decreasing their consumption and frequency of on-the-job leisure, in order to have more leisure outside their workplaces.

To test this hypothesis, we estimate OLS equation models as follows:

$$E_i = \mu + \beta_1 X_i + \beta_2 Educ_i + \beta_3^{'} D_{t,i} + \beta_4^{'} D_{t,i} * Educ_i + \varepsilon_i \quad (2)$$

where E_i is a measure of work effort (either the consumption or frequency of on-the-job leisure) for respondent i, and $Educ_i$ represents dummy variables to control for the education of workers. $\beta_3^{'}$ is a vector of dummy variables for decade. The coefficients of interest are the vector $\beta_4^{'}$ on the interaction of survey dummies $D_{t,i}$ with the dummy variables of education. We consider three levels of education: workers with primary education (less than 12 years of education) as reference group, comparing them with workers with secondary education (12-15 years of education) and university education (16 and more years of education).

Panel A of Table 5 presents the results of estimating Equation (2) for individuals based on differences in educational attainment. Although we find that some of the interaction terms are statistically significant, the results do not help to explain the documented trends in on-the-job leisure during this period, since if we are to explain these observed trends we should expect the interaction terms to be statistically significant throughout the period.

3.2.2. The role of children

Another explanation of the patterns observed for on-the-job leisure is the rise in parental time investments (Guryan et al., 2008). Increases in parental time spent in human capital-enhancing activities are mainly viewed as a result of increases in returns to investment in children over time (Chiappori et al., 2017; Doepke and Zilibotti, 2017). Parents may have experienced larger decreases in the consumption and frequency of on-the-job leisure, compared to non-parents, because they are likely to strive to have more time available to spend with their children. This could mean that they are working harder, resulting in less

on-the-job leisure, since they are trying to finish their work obligations sooner in order to maximize the time spent with their children.

To test this hypothesis, we estimate OLS equation models as follows:

$$E_i = \mu + \beta_1 X_i + \beta_2 Children_i + \beta_3^{'} D_{t,i} + \beta_4^{'} D_{t,i} * Children_i + \varepsilon_i \qquad (3)$$

where E_i is a measure of work effort (either the consumption or frequency of on-the-job leisure) for respondent i, and $Children_i$ is a dummy variable to control for the presence of children in the worker's household (value '1' if there is a child under age 5 in the household and value '0' otherwise). $\beta_3^{'}$ is a vector of dummy variables for decades. The coefficients of interest are the vector $\beta_4^{'}$ on the interaction of survey dummies $D_{t,i}$ with the dummy variable controlling for the presence of children.

Panel B of Table 5 presents the results of estimating Equation (3) for individuals based on the presence of children. Again, although we find that some of the interaction terms are statistically significant, the results do not help to explain the documented trends in on-the-job leisure during this period, since the interaction terms should be statistically significant across the whole period.

3.2.3. Changes in the composition of leisure outside the job place

We also test whether our results are driven by secular declines in leisure outside of work, particularly for those in routine task-intensive occupations. We develop a more comprehensive picture of how workers allocate their work and leisure, and we consider whether there are any potential offsetting effects of work during leisure hours. These offsetting effects of work during leisure hours could have increased more for workers in some high-paying, non-routine professional occupations, which could have affected work satisfaction differently. Sevilla et al. (2012) show decreases in leisure overall in the US between the 1960s and the 2000s, but more so for the highly educated. Thus, we look at whether declines in leisure outside of work have been less so for routine task-intensive occupations.

To that end, we compute the time devoted to off-the-job leisure, which is defined as the period before and after work. The definition of leisure is similar to the definition of on-the-job leisure (social leisure, active leisure, and passive leisure), although restricted

to activities that are done before or after work. Table 6 shows the evolution of the time devoted to off-the-job leisure, off-the-job meals, and off-the-job leisure and meals. We observe a decrease in off-the-job leisure and meals between the 1980s and the 2000s, consistent with prior research showing decreases in leisure time in the UK (Giménez-Nadal and Sevilla, 2012; Fang and McDaniel, 2017). We have evidence that leisure has decreased both in and outside of the workplace, indicating that lost leisure in the workplace is not being made up for outside of work.

In Table 7, we examine the relationship between the routine task-intensity of an occupation and the time devoted to off-the-job leisure and/or meals, as estimated by Equation (1), with the dependent variable being the time devoted to off-the-job leisure during working days. Our results show that the decrease in off-the-job leisure and/or meals is not linked to the routine task-intensity of the occupation. We also focus on the time devoted to off-the-job meals, looking at whether declines in off-the-job meals have been less so for routine task-intensive occupations. We estimate the time devoted to off-the-job meals as in Equation (1), and Column (2) shows that neither the amount nor the decrease in off-the-job meals are affected by non-routine task-intensity. Finally, we combine both off-the-job leisure and meals (Column (3)), and results are consistent with the use of this alternative definition of off-the-job free time (leisure and meals). Thus, we find that the routine task-intensity of the occupation is not related to the amount of leisure outside of work nor to the reported decrease in this leisure.

One issue that remains from this analysis relates to part-time work, since some workers may choose to go part-time in response to increasing work intensification. We have replicated the results shown in Tables 6 and 7 with a sample of both full-time and part-time workers and results are robust (see Tables A8 and A9 of the Supplementary Appendix).[15]

Another question that emerges from our analysis is that of the location of work. The adoption of ICT technologies has allowed for a relocation of jobs from workplaces to other places, including working from home and working while travelling. The analysis of the current data shows that the proportion of work done in the workplace has decreased

[15] The analysis of the sample shows that the percentage of part-time workers has decreased decade by decade, with 37% of the workers in the sample working part-time in the 1980s, while only 18% of the workers in the sample worked part-time in the 2010s. These figures differ from those reported by official statistics, which may indicate that the sample of part-time workers is not representative, and thus results must be taken with caution.

from 89.67% in the 1980s to 79.32% in 2010, while the proportion of work done at home or travelling has decreased by 8.41% and 3.37%, respectively (see Table A10 in Supplementary Appendix). These trends may indicate that ICT technology adoption may be behind the observed trends in the consumption and frequency of on-the-job leisure, especially for those whose work entails moving between multiple locations in a day, or spending time in vehicles while working. However, additional analyses excluding workers working from home (Table A11 in Supplementary Appendix) indicate that ICT is not the only factor at the root of the evolution of on-the-job leisure.

3.3. The Skills and Employment Surveys

Drawing on the Skills and Employment Survey Series, Green et al. (2022) analyse the evolution of work effort in the UK. This survey series contains data on the skills and employment experiences of Britons aged 20-65 for the years 1986, 1992, 1997, 2001, 2006, 2012, and 2017. The authors use this data to calculate several indicators related to work intensification in the UK, such as technological change (e.g. computerized and/or automated technology), the closer control and discipline afforded by modern forms of management (e.g. Just In Time (JIT) and Total Quality Management (TQM)), and team cooperation and discipline, together with incentive pay, target-setting, and other elements of the high-involvement package, such as upskilling, the organization's changing environment (e.g. greater external competitive pressure), and the type of employment.

However, only three indicators can be computed in all the decades. These are: 'New automated equipment' (the proportion of workers answering 'yes' to the question about new computerized equipment during the previous five years), the presence of unions at the workplace (the percentage of workers answering 'yes' to the question about unions or staff associations), and the proportion of workers with permanent contracts. We compute the average value for the different SES years and link them to the Time Use Survey data. Specifically, the average value of the SES 1986 is linked to the TUS 1983 and TUS 1986 data, the average value of the SES 1992 and SES 1997 is linked to the TUS 1995, the average value of the SES 2001 is linked to the 2000 TUS, the average value of the SES 2006 is linked to the TUS 2005, and the average value of the SES 2012 and SES 2017 is linked to the TUS 2015. We estimate OLS regressions to examine the consumption and frequency of on-the-job leisure, controlling for the socio-demographic factors used in

Equation (1), and the three variables obtained from SES series. Our proxy variable for automation/technological change (i.e. computer use at work) is computed for each period of time, and given that it changes over time we estimate an OLS model, where the variable is introduced directly as an explanatory variable.

Table 8 shows that the introduction of computerized and/or automated equipment is associated with a decrease in the consumption and frequency of on-the-job leisure (less consumption of on-the-job leisure, fewer number of breaks for on-the job leisure, and more time working until consuming on-the-job leisure).

The empirical evidence indicates that the introduction of computerized and automated equipment is linked to reduced leisure and increased work effort, supporting the hypothesis that technological change drives higher work dedication. Conversely, stronger labor unions, staff associations, and permanent contracts are associated with increased leisure and consumption. This implies that declining union influence intensifies work effort in the UK, while permanent contracts signal job security and greater leisure, suggesting that temporary contracts signify job insecurity and higher work pressure.

4. Conclusions

This paper, using detailed diary information on what workers do while at work, documents a decrease in the daily amount of time spent in the consumption of on-the-job leisure in the UK since the 1980s. The number of on-the-job leisure spells also decreased, and workers worked for longer before taking a break. We also show that the decrease in the frequency of on-the-job leisure is much greater for workers in routine task-intensive occupations. All in all, the results are consistent with the automation of job tasks as a factor underlying the increase in workers' effort during the analysed period. By revealing increases in work effort, our results add to the losses from routine-biased technological change for workers in middle-wage occupations, beyond the increases in wage inequality and unemployment, and posit routine-biased technological change as a factor behind the trends in work intensification in the UK.

One question that emerges from this analysis is why this channel contributes to work intensification in jobs high in routine-task content, such as office clerks. These jobs can be characterized as having easy-to-monitor task performance from the outset. Thus, it

could be that the RBTC also affects the task content of the occupations (Autor et al., 2003; Acemoglu and Autor, 2011), changing its composition (Acemoglu and Restrepo, 2019,2020). The current analysis and data do not allow us to test whether work intensification in the UK comes from a more efficient allocation of job tasks, from the changing composition of job tasks, or from both. We leave this issue for future research.

One limitation of the current analysis is that old time-use surveys do not include enough information about workers, such as the type of contract. It would be interesting to analyse whether the findings could be different for workers on permanent contracts compared to those with fixed-term or zero-hours contracts, since effort and routinization may affect these workers differently. The analysis using the SES series indicates that a higher proportion of workers with permanent contracts is related to a higher frequency of on-the-job leisure. Furthermore, there are uneven time gaps between the time use surveys used (the shortest is 4 years and the longest is 10 years), and while these gaps may appear relatively short, many things may have happened that are relevant for our analysis. For instance, in the period between 1987 and 1995, many workplaces in the UK adopted personal desktop computers, and in the decade between surveys in 2005 and 2015 the use of smartphones may have transformed how people perform their jobs, for instance by having access to email on a 24/7 basis. These are only two examples of technological and societal changes that took place in the periods between the surveys. Unfortunately, time use surveys are costly to implement, and their availability is scarce.

Moreover, wages of workers, or the pay structure, may also be relevant in the current context, as the consumption of on-the-job leisure probably depends on pay. However, the surveys used here do not contain information on wages or pay structure, and thus we leave this issue for future research. Additionally, it is possible that other unobserved person-fixed-effects within occupation–industry cells, which are not controlled for, may induce biases, and no appropriate instruments for the explanatory variables are available. Finally, the COVID-19 pandemic has led to an increase in the proportion of individuals who work from home (Aksoy et al. 2021), which may affect worker effort as we measure it in the current context, and thus it would be interesting to analyse this. However, this cannot be accomplished from the current data, since surveys do not cover the COVID-19 period, and the topic must, again, be left for future research.

In the future, investing in human capabilities and new capital is a more effective growth strategy than attempting to get people to work harder, though this has had unequal effects for workers (Green et al., 2022). Nevertheless, there is still room for work intensification, so policymakers and researchers must be vigilant in monitoring this aspect of job quality. A more positive outcome could be achieved if there was a move to allow trade unions to bargain over working conditions, or if employers embraced job re-design. Additionally, providing workers with better social support, giving them more task discretion, and offering opportunities for organizational participation could reduce the detrimental effects of work intensification on well-being.

Supplementary material

Supplementary material is available on the OUP website. These are the replication files and the online appendices.

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Conflict of interest

The authors declare no conflicts of interest.

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Table 1. Example of the consumption and frequency of on-the-job leisure

(1) Start time	(2) Finish time	(3) Activity type	(4) Duration
8:00 a.m.	11:00 a.m.	Paid work	3.00
11:00 a.m.	11:20 a.m.	Meals or snacks in other places	0.33
11:20 a.m.	12:00 p.m.	Relax/do nothing	0.66
12:00 p.m.	2:10 p.m.	Paid work	2.16
2:10 p.m.	2:20 p.m.	Work breaks	0.16
2:02 p.m.	4:40 p.m.	Paid work	2.33
Time at work (hours)			8.67
Time working (hours)			7.50
Consumption of on-the-job leisure (hours)			1.16
Number of on-the-job leisure episodes			2.00
Working time until consuming on-the-job leisure (hours)			2.50

Notes: *Time at work* measures the time from the moment a worker begins work until the time a worker stops working on a given diary day. *Time working* measures the time that the worker spends in market work activities while at work. *Consumption of on-the-job leisure* is the amount of time the respondent spends not working while at work. The *number of on-the-job leisure episodes* is constructed as the number of spells of non-work activities while at work. *Working time until consuming on-the-job leisure* is computed by dividing the total amount of time spent working by the number of work spells in a given diary day.

Table 2. Consumption and frequency of on-the-job leisure over time, the UK

	(1)		(2)		(3)		(4)		(5)	(6)
	Decade 1980s		**Decade 1990s**		**Decade 2000s**		**Decade 20010s**		**Diff 2010s-1980s**	**P-value diff**
Time at work	8.76	(0.06)	9.44	(0.14)	8.81	(0.05)	8.39	(0.08)	-0.37	(<0.01)
Working Time	7.40	(0.04)	8.43	(0.12)	7.80	(0.04)	7.23	(0.07)	-0.17	(0.05)
Consumption of on-the-job leisure	1.36	(0.03)	1.00	(0.07)	1.00	(0.02)	1.16	(0.04)	-0.20	(<0.01)
Frequency of on-the-job-leisure										
Number of on-the-job leisure episodes	1.69	(0.02)	1.08	(0.05)	1.10	(0.02)	1.31	(0.03)	-0.38	(<0.01)
Working time until consuming on-the-job leisure	3.31	(0.04)	5.03	(0.14)	4.62	(0.04)	3.89	(0.07)	0.58	(<0.01)
Number of diaries	2,836		494		4,810		1,692			
Number of workers	618		494		4,138		1,381			

Notes: Data come from the 1983, 1987, 1995, 2000, 2005 and 2015 UK time diary surveys. The sample are full-time workers aged 21-65. We select working days in which there are at least 60 minutes of market work activities, excluding commuting. *Time at work* measures the time from the moment a worker begins work until the time a worker stops working in a given diary day. *Time working* measures the time that the worker spends in market work activities while at work. *Consumption of on-the-job leisure* is the amount of time the respondent spends not working while at work. The *number of on-the-job leisure episodes* is constructed as the number of spells spent on non-work activities while at work. *Working time until consuming on-the-job leisure* is computed by dividing the total amount of time spent working by the number of work spells in a given diary day.

Table 3. Consumption and frequency of on-the-job leisure over time: the role of RBTC

	(1)	(2)	(3)
	Amount	*Frequency*	
	Consumption of on-the-job leisure	*Number of breaks for on-the-job leisure*	*Working time until consuming on-the-job leisure*
RTI	0.03	0.19***	-0.44***
	(0.05)	(0.05)	(0.08)
Decade's 2000's	-0.37***	-0.60***	1.32***
	(0.07)	(0.06)	(0.12)
Decade's 2010's	-0.27***	-0.35***	0.64***
	(0.08)	(0.06)	(0.13)
RTI *Decade 2000's	-0.08	-0.15***	0.27***
	(0.06)	(0.05)	(0.09)
RTI*Decade 2010's	-0.09	-0.22***	0.44***
	(0.07)	(0.06)	(0.11)
Number of observations	4,926	4,926	4,926
Number of workers	3,817	3,817	3,817
R-Squared	0.03	0.11	0.20

Notes: Robust standard errors in parenthesis. Data come from the 1983, 2000 and 2015 UK time diary surveys. The sample are full-time workers aged 21-65. We select working days in which there are at least 60 minutes of market work activities, excluding commuting. *Consumption of on-the-job leisure* is the amount of time the respondent spends not working while at work. The *number of on-the-job leisure episodes* is constructed as the number of spells spent on non-work activities while at work. *Working time until consuming on-the-job leisure* is computed by dividing the total amount of time spent working by the number of work spells in a given diary day. We estimate the following OLS regression: $E_i = \mu + \beta_1 X_i + \beta_2 RTI_i + \beta_3 D_{t,i} + \beta_4 D_{t,i} * RTI_i + \varepsilon_i$, where E_i represents either the consumption or the frequency of on-the-job leisure (either the number of on-the-job leisure episodes or work time before consuming on-the-job leisure) for respondent i. The vector X_i includes person-specific socio-demographic characteristics. RTI_i is the Routine Task index measure. *Significant at the 10% level; **significant at the 5% level; ***Significant at the 1% level.

Table 4. Consumption and frequency of on-the-job leisure over time: RBTC and change in employment

	(1)	(2)	(3)
	Amount	*Frequency*	
	Consumption of on-the-job leisure	*Number of breaks for on-the-job leisure*	*Working time until consuming on-the-job leisure*
RTI	0.03	0.19***	-0.27***
	(0.05)	(0.05)	(0.08)
Change in Employment	-0.73	-1.16*	1.58
	(0.91)	(0.66)	(1.35)
Decade 2000s	-0.35***	-0.58***	1.05***
	(0.07)	(0.06)	(0.11)
Decade 2010s	-0.24***	-0.30***	0.58***
	(0.09)	(0.07)	(0.13)
RTI *Decade 2000s	-0.08	-0.15***	0.16*
	(0.06)	(0.05)	(0.09)
RTI *Decade 2000s*Change in Employment	2.01	1.01	-2.56
	(1.53)	(1.01)	(2.37)
RTI*Decade 2010s	-0.11	-0.26***	0.29***
	(0.08)	(0.06)	(0.11)
RTI*Decade 2010s*Change in Employment	0.61	0.78	-0.84
	(0.82)	(0.56)	(1.06)

Notes: Robust standard errors in parenthesis. Data come from the 1983, 2000 and 2015 UK time diary surveys. The sample are full-time workers aged 21-65. We select working days in which there are at least 60 minutes of market work activities, excluding commuting. *Consumption of on-the-job leisure* is the amount of time the respondent spends not working while at work. The *number of on-the-job leisure episodes* is constructed as the number of spells spent on non-work activities while at work. *Working time until consuming on-the-job leisure* is computed by dividing the total amount of time spent working by the number of work spells in a given diary day. We estimate the following OLS regression: $E_i = \mu + \beta_1 X_i + \beta_2 RTI_i + \beta_3 D_{t,i} + \beta_4 D_{t,i} * RTI_i + \beta_5 D_{t,i} * RTI_i * Change\ in\ Employment_i + \varepsilon_i$, where E_i represents either the consumption or the frequency of on-the-job leisure (either the number of on-the-job leisure episodes or work time before consuming on-the-job leisure) for respondent i. The vector X_i includes person-specific socio-demographic characteristics. RTI_i is the Routine Task index measure for occupation 'i', and *Change in Employment*$_i$ measures the percent change in employment share for occupation 'i' in comparison to 1985 *Significant at the 10% level; **significant at the 5% level; ***Significant at the 1% level

Table 5. Consumption of on-the-job leisure over time, by educational attainment and presence of children <5

	(1)	(2)	(3)
	Amount	*Frequency*	
	Consumption of on-the-job leisure	*Number of breaks for on-the-job leisure*	*Working time until consuming on-the-job leisure*
	Panel A: Analysis by education		
Secondary education	0.05	-0.05	-0.05
	(0.07)	(0.05)	(0.10)
University education	0.27***	-0.06	0.11
	(0.08)	(0.05)	(0.10)
Decade 1990s	-0.59***	-0.61**	1.51**
	(0.19)	(0.29)	(0.76)
Decade 2000s	-0.51***	-0.69***	1.48***
	(0.07)	(0.05)	(0.11)
Decade 2010s	-0.47**	-0.51***	0.28
	(0.19)	(0.16)	(0.33)
Secondary education*Decade 1990s	(0.33)	(0.06)	(0.50)
	(0.21)	(0.30)	(0.78)
Secondary education*Decade 2000s	0.11	0.02	0.06
	(0.09)	(0.07)	(0.14)
Secondary education*Decade 2010s	0.02	-0.09	0.98***
	(0.20)	(0.17)	(0.35)
University education*Decade 1990s	0.53**	(0.21)	(0.63)
	(0.26)	(0.31)	(0.81)
University education*Decade 2000s	0.15	0.07	-0.25*
	(0.10)	(0.07)	(0.14)
University education*Decade 2010s	0.23	0.17	0.35
	(0.21)	(0.17)	(0.34)
Number of observations	9,832	9,832	9,832
Number of workers	6,631	6,631	6,631
R-Squared	0.04	0.13	0.35
	Panel B: Analysis by the presence of children <5		
Children <6	0.05	-0.13*	0.22
	(0.04)	(0.05)	(0.21)
Decade 1990s	-0.19***	-0.54***	1.00***
	(0.02)	(0.05)	(0.16)
Decade's 2000s	-0.39***	-0.66***	1.38***
	(0.04)	(0.06)	(0.18)
Decade's 2010s	-0.26***	-0.43***	0.92***
	(0.01)	(0.04)	(0.10)
Decade 1990s *Children <6	-0.07*	0.32***	-0.55**
	(0.03)	(0.04)	(0.20)
Decade's 2000s *Children <6	-0.06	0.02	0.12
	(0.10)	(0.07)	(0.23)
Decade's 2010s *Children <6	-0.30***	-0.01	-0.20
	(0.04)	(0.05)	(0.21)
Number of observations	9,832	9,832	9,832
Number of workers	6,631	6,631	6,631
R-Squared	0.04	0.13	0.20

Notes: Robust standard errors in parenthesis. Data come from the 1983, 1987, 1995, 2000, 2005 and 2015 UK time diary surveys. The sample are full-time workers aged 21-65, and in working days defined as those with at least 60 minutes to market work activities, excluding commuting. *Consumption of on-the-job leisure* is the amount of time the respondent spends not working while at work. The *number of on-the-job leisure episodes* is constructed as the number of spells spent on non-work activities while at work. *Working time until consuming on-the-job leisure* is computed by dividing the total amount of time spent working by the number of work spells in a given diary day. We estimate the following OLS regression: $E_i = \mu + \beta_1 X_i + \beta_2 SF_i + \beta_3' D_{t,i} + \beta_4' D_{t,i} * SF_i + \varepsilon_1$, where E_i represents either the consumption or the frequency of on-the-job leisure (either the number of on-the-job leisure episodes or work time before consuming on-the-job leisure) for respondent i in period t. The vector $X_{i,t}$ includes person-specific socio-demographic characteristics. SF refers to the supply factor analysed. *Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level.

Table 6. Trends in off-the-job leisure and eating

	(1)		(2)		(3)		(4)		(5)	(6)
	Decade 1980s		**Decade 1990s**		**Decade 2000s**		**Decade 2010s**		**Diff 2010s-1980s**	**P-value diff**
Leisure outside of work	3.98	(2.23)	3.78	(2.44)	3.76	(2.23)	3.51	(2.24)	-0.47	(<0.01)
Meals outside of work	0.77	(0.67)	0.62	(0.52)	0.72	(0.61)	0.79	(0.78)	0.02	(0.46)
Leisure + meals outside of work	4.75	(2.34)	4.40	(2.57)	4.48	(2.35)	4.30	(2.45)	-0.45	(<0.01)
Number of diaries	2,836		512		4,810		1,692			
Number of workers	618		495		4,138		1,380			

Notes: Data come from the 1983, 1987, 1995, 2000, 2005 and 2015 UK time diary surveys. The sample are full-time workers aged 21-65. We select working days in which there are at least 60 minutes of market work activities, excluding commuting. *Leisure in non-work time* includes the time devoted to social leisure, active leisure, and passive leisure, but outside the job.

Table 7. Consumption of off-the-job leisure over time

	(1)	(2)	(3)
	Leisure	*Meals*	*Leisure+Meals*
RTI	-0.01	0.00	-0.01
	(0.09)	(0.03)	(0.08)
Decade 2000s	-0.11	-0.07**	-0.19**
	(0.10)	(0.04)	(0.09)
Decade 2010s	-0.39***	-0.08**	-0.47***
	(0.11)	(0.04)	(0.11)
RTI *Decade 2000s	0.05	-0.03	0.02
	(0.09)	(0.03)	(0.09)
RTI*Decade 2010s	0.12	-0.02	0.10
	(0.11)	(0.04)	(0.10)
Number of observations	4,926	4,926	4,926
Number of workers	3,817	3,817	3,817
R-Squared	0.326	0.106	0.379

Notes: Robust standard errors in parenthesis. Data come from the 1983, 2000 and 2015 UK time diary surveys. The sample are full-time workers aged 21-65. We select working days in which there are at least 60 minutes of market work activities, excluding commuting. *Consumption of on-the-job leisure* is the amount of time the respondent spends not working while at work. We estimate the following OLS regression: $E_i = \mu + \beta_1 X_i + \beta_2 RTI_i + \beta_3 D_{t,i} + \beta_4 D_{t,i} * RTI_i + \varepsilon_i$, where E_i represents either off-the-job leisure or off-the-jog meals, or the sum of the two categories for respondent i. The vector X_i includes person-specific socio-demographic characteristics. RTI_i is the Routine Task Index measure. *Significant at the 10% level; **significant at the 5% level; ***Significant at the 1% level.

Table 8. Results using SES surveys

	(1)	(2)	(3)
	Amount	*Frequency*	
	Consumption of on-the-job leisure	*Number of breaks for on-the-job leisure*	*Working time until consuming on-the-job leisure*
Introduction of computers/automated equipment	-1.14***	-2.95***	4.67***
	(0.37)	(0.26)	(0.53)
Unions or staff associations at workplace	1.52**	2.96***	-4.65***
	(0.77)	(0.55)	(1.12)
Permanent contracts	0.67	12.80***	-15.31***
	(3.77)	(2.64)	(5.93)
Observations	9850	9850	9850
R-squared	0.042	0.125	0.348

Notes: Data come from the 1983, 1987, 1995, 2000, 2005 and 2015 UK time diary surveys. The sample are full-time workers aged 21-65. We select working days in which there are at least 60 minutes of market work activities, excluding commuting. Consumption of on-the-job leisure is the amount of time the respondent spends not working while at work. The number of on-the-job leisure episodes is constructed as the number of spells spent on non-work activities while at work. Working time until consuming on-the-job leisure is computed by dividing the total amount of time spent working by the number of work spells in a given diary day. SES data includes the years the years 1986, 1992, 1997, 2001, 2006, 2012 and 2017. *Introduction of computers/automated equipment* is obtained from the question that asked whether, over the previous five years, 'new computerised or automated equipment was introduced into the workplace' and computed as the proportion of workers answering 'yes' to this question. *Unions or staff associations at workplace* is measured as the percentage of workers answering 'yes' to the question 'whether are unions or staff associations at workplace'. *Permanent contracts* is measured as the proportion of workers with permanent contracts. We estimate the following OLS regression: $E_i = \mu + \beta_1 X_i + \beta_2 D_{t,i} + \varepsilon_i$, where E_i represents either the consumption or the frequency of on-the-job leisure (either the number of on-the-job leisure episodes or work time before consuming on-the-job leisure) for respondent i in period t. The vector X_i includes person-specific socio-demographic characteristics. *Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level.