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Working from home and well-being during the pandemic and beyond: a longitudinal analysis in five countries

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Abstract

Background Given the rise of remote work in the wake of the COVID-19 pandemic, many studies have investigated how working from home (WFH) is related to employee well-being. So far, findings have been mixed and based predominantly on cross-sectional analyses.

Methods We used multi-level regression models to describe the longitudinal relationship between WFH and well-being over 11 assessments from April 2020 to November 2023, based on a unique, population-based sample of $N = 3403$ employed participants from five European countries.

Results Even after controlling for relevant covariates, WFH was negatively related to well-being in the initial stages of the pandemic, but unrelated to WFH thereafter.

Conclusion Our analysis offers a differentiated picture on within- and between-person dynamics of WFH and well-being over the course of the pandemic and beyond and can inform the discussion how individuals, organizations, and societies can prepare for a future in which WFH plays a more prominent role.

Keywords Working from home, Well-being, COVID-19, Longitudinal studies, Occupational health

Before the COVID-19 pandemic, working from home (WFH) was not a completely unknown phenomenon [1, 2]. Still, WFH was rather the exception than the rule [3, 4]. With the onset of the COVID-19 pandemic, however, "home office" became the norm for many, mostly white-collar office workers, and the number of employees who performed telework in the EU doubled between 2020 and 2021 [3, 4]. WFH appears to be here to stay, with many companies downsizing their office space and adopting enduring policies regarding remote work, profoundly changing the conceptualization of the workplace [5–7].

The accelerated dissolution of the traditional workplace has increased the urgency of understanding the consequences of WFH for well-being. The current study therefore adds to the extensive existing literature by describing the longitudinal relationship between WFH and well-being across a three-year period based on a unique population-based sample representative for gender and region of residence from five European countries. Participants reported their main place of work, their life satisfaction, and psychological distress every three months starting

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in April 2020, at the height of the first lockdowns, and continuing through the next three years until July 2023, that is, after the pandemic was officially declared over. The density of our measurements allows us to decompose the relationship between WFH and well-being into its within- and between-person components. Thus, our findings provide a multifaceted, nuanced approach to the relationship between WFH and well-being, considering pandemic and post-pandemic dynamics.

Previous research on working from home and well-being

Many terms have been used to refer to paid work that is flexibly performed outside the premises of the employer, such as WFH, telework, home office, or remote work [8, 9]. In line with the Eurofound definition of telework [3], we refer to WFH as "*a work arrangement in which work is carried out totally or partially from home with the support of ICT [Information and Communication Technologies] and partially or never from the employer's premises*" (p. 4).

Many studies have investigated how WFH is associated with well-being [10–17]. Together, the results of existing studies and reviews indicate that the relationship between WFH and well-being is far from straightforward [8]. For example, WFH reduces commuting time and thus increases available for leisure activities, such as physical activity, which might decrease stress [18–20]. Moreover, various studies show that increased autonomy, flexibility, and work-life balance due to WFH can have a positive impact on well-being [11]. On the downside, however, WFH may contribute to blurred boundaries between private and work life, which could increase stress [21, 22]. In addition, the workplace is also an important source of social interaction; co-workers can be a source of social and instrumental support [23]. WFH may therefore contribute to loneliness and social isolation. Constant exposure to technology might also negatively affect well-being [13].

It is currently difficult to summarize existing findings on the overall relationship between WFH and well-being, as the relationship may depend on how well-being is operationalized (e.g., cognitive versus affective well-being; global versus experiential assessments). Drawing conclusions about the overall relationship between WFH and well-being is further complicated by the fact that much of the recent research has been cross-sectional and was conducted during specific phases of the COVID-19 pandemic. Especially at the beginning of the pandemic, WFH was closely related to various confinement and social distancing measures and thus, often a mandate rather than a choice [14, 20, 24–26]. Due to school closures and reductions in ambulatory care services, people with children and other care duties often had to perform "double duty" during their work time, which increased stress and negatively impacted well-being [27, 28]. For those living alone, WFH in addition to other existing social distancing measures might have led to feelings of social isolation and loneliness [29]. Thus, WFH might have affected well-being differently during compared to before and after the pandemic, which limits the informative value of cross-sectional studies typical of the literature so far. Furthermore, the relationship between WFH and well-being may differ across occupations and subpopulations; it is therefore problematic that many existing studies have been based on single countries and selective samples (for an exception, see [30]).

So far, just a handful of longitudinal studies have examined the relationship between WFH and well-being during the pandemic based on representative samples. Using 19-year panel data from the Household, Income, and Labour Dynamics in Australia survey, Bilgrami [24] found that WFH was unrelated to pre-pandemic well-being (operationalized as a composite score derived from various scales of mental health) but negatively related to well-being during the pandemic. In another study based on three waves of data collection in six population-based surveys in the United Kingdom, Wels and colleagues [31] found no evidence that WFH was related to psychological distress during the first Covid-19 lockdown in 2020, or in the period from July to October 2020. However, WFH was positively related to psychological distress during the second COVID-19 lockdown in November 2020. Based on the first four waves of the multinational dataset used in the current study, Schifano and colleagues [28] found that, cross-sectionally, WFH was negatively related to well-being (operationalized via indicators of loneliness, anxiety, depression, life satisfaction and the estimation of one's life as worthwhile). Longitudinally, however, participants who switched from office work to WFH between April to December 2020 decreased in anxiety. Together, existing longitudinal findings illustrate the importance of a dynamic approach to investigations of WFH and well-being [22, 32].

Current study

In the current study, we add to the literature on WFH and well-being by providing dense, longitudinal data from population-based samples from five European countries, covering 11 measurement occasions over the course of the pandemic and beyond. This study thus goes beyond the analyses presented in Schifano and colleagues [28], by adding seven more waves of data, moving beyond times of pandemic restrictions. Given the dearth of longitudinal studies of WFH and well-being, we focus on the dynamics of the direct relationship between WFH and well-being. Our main aim was to separate the within- and between-person relationships between WFH and well-being. That is, we simultaneously examine the extent to which within-person fluctuations in WFH correspond within within-person fluctuations in well-being during and beyond the pandemic, as well as how persons' *average* level of WFH corresponds with their trajectory of well-being during and beyond the pandemic. We consider two conceptually distinct measures of well-being; specifically, an indicator of psychological distress (depressive symptoms, anxiety, perceived stress), as well as life satisfaction as a cognitive evaluation of well-being [12, 33]. Our data allow us to investigate the dynamic relationship of WFH and distinct aspects of well-being over time in a large and diverse population from different countries. Given mixed findings from previous studies regarding the magnitude and nature of the relationship between WFH and well-being, we did not specify any hypotheses about either the direction or linearity of the relationships [8].

Methods

Data source

The current study was based on data from the COME-HERE study [34]. The COME-HERE study is a multinational, longitudinal study of work and well-being that was initiated at the beginning of the COVID-19 pandemic and has regularly followed participants ever since. Participants (N = 8,063 at the first wave) were recruited by Qualtrics from their online market research panel in France (n = 1706), Germany (n = 1720), Italy (n = 1710), Spain (n = 1711), and Sweden (n = 1216). Each country sample at Wave 0 was drawn to be nationally representative regarding age, gender, and region of residence. According to official statistics [35], the baseline sample was representative of the population with regard to its gender composition and regional distribution. However, the baseline sample was slightly younger than the population (for details, see Additional Materials on the Open Science Framework at https://osf.io/k3fvr/?view_only=cbee2a22a09e4f47b44c7756b93134e0).

Upon providing informed consent, participants received a link to the survey. Participants completed several questionnaires covering different topics, depending on the measurement occasion. At the beginning of the study, the questionnaires focused primarily on pandemic-related topics such as reaction to confinement measures. At later stages, the questionnaires covered other topics, such as attitudes toward vaccination. Questionnaires were originally drawn up in English and translated and back-translated by bilingual individuals into German, French, Italian, Spanish, and Swedish. COME-HERE was approved by the Ethics Research Panel of the University of Luxembourg, decision number erp 20–026 c/a come-here. We confirm that all research was performed in accordance with the relevant guidelines and regulations.

So far, 13 waves of data have been collected, 11 of which were available for the current study: Wave 0 (April 27-May 6, 2020), Wave 1 (June 9–15, 2020), Wave 2 (August 8–24, 2020), Wave 3 (November 19-December 16, 2020), Wave 4 (February 26-March 22, 2021), Wave 5 (June 1–28, 2021), Wave 6 (October 14-November 9, 2021), Wave 7 (February 8-March 6, 2022), Wave 8 (June 7-July 8, 2022), Wave 9 (November 28-December 19, 2022), and Wave 10 (June 8-July 28, 2023).

The COME-HERE data contain sensitive individual information and cannot be made publicly available (Ethics Research Panel of the University of Luxembourg, decision number erp 20–026 c/a come-here). Data access on the University of Luxembourg server can be obtained to reproduce the present analyses by contacting the Department of Behavioral and Cognitive Sciences (dbcs.secretariat@uni.lu). Statistical code to reproduce the presented analyses, analyses outputs as well as information on the stay-at-home restrictions used are available via the Open Science Framework at https://osf.io/k3fvr/?view_only=cbee2a22a09e4f47b44c7756b93134e0.

Sample

The sample consisted of the COME-HERE participants from all five countries who reported that they were employed full- or part-time in either the public or private sector, and for whom data on WFH was available for at least one wave (N = 3403 participants; Z = 21,503 observations). Participants ranged in age from 18 to 88 years (M = 43.31, SD = 12.02; 2.4% were older than 65 years). About half (51.2%) identified as female, and about half (49.9%) had a tertiary degree. Sample characteristics are displayed in Table A1.

Participants took part in M = 6.32 waves (SD = 2.93, range: 1–11). The vast majority (79.0%) took part in at least four waves. Participants who did not complete the survey at one point in time were still invited to take part in subsequent waves. Sample size at each wave was: n = 2701 (Wave 0), n = 1919 (Wave 1), n = 2307 (Wave 2), n = 2753 (Wave 3), n = 2457 (Wave 4), n = 2109 (Wave 5), n = 2013 (Wave 6), n = 1811 (Wave 7), n = 1642 (Wave 8), n = 1465 (Wave 9) and n = 326 (Wave 10).

Measures

Life satisfaction

At each wave, participants used a scale ranging from 0 (not at all) to 10 (completely) to indicate their *overall satisfaction with life* in the past week (single item – "Overall, in the past week, how satisfied have you been with your life?").

Distress

Three indicators of psychological distress were assessed at each wave. Scores on the GAD-7 (7 items [36]), were used as a measure of *anxiety*. Scores on the Patient Health Questionnaire (9 items [37]), were used as an indicator *of depression*. Scores on the Perceived Stress Scale (10 items [38]), were used as a measure of *perceived stress*. The three scale scores were highly correlated (r=.66 –.84 based on the sample of observations) and loaded onto a single factor which explained 73.6% of the variance (factor loadings: 0.73 – 0.92; see Appendix for more information). We therefore used the regression method to calculate factor scores as a measure of *distress*. By default, SPSS z-standardizes factor scores.

Working from home

Beginning in Wave 3, participants retrospectively assessed where they had worked for each month between February 2020 and May 2023 ("In each of the following months, where did you mostly work?" *At home*, *not at home*, *I was not working*). Due to error, no data on the primary place of work was collected for June 2021. Whether or not participants had worked mostly from home in the months of February through November 2020 was assessed in both Waves 3 and 4. Under the assumption that the accuracy of retrospective assessments decreases over time, we used the data from Wave 3 whenever available. The other retrospective assessments took place in Wave 4 (for December 2020 – February 2021), Wave 5 (for March – May 2021), Wave 6 (for July – September 2021), Wave 7 (for October 2021 – January 2022), Wave 8 (for February – May 2022), Wave 9 (for June – October 2022) and Wave 10 (November – May 2023). We recoded responses to create a dummy variable (working from home, WFH; yes = 1, no = 0).

To analyze the relationship between WFH on the one hand, and the dependent variables life satisfaction and distress on the other hand, it was necessary to have the variables on the same time metric. We therefore used the monthly WFH data to calculate a measure of the *intensity of WFH* for each wave. Specifically, we calculated the average months WFH in the months after the previous wave up until the next wave. For example, the Wave 0 WFH measure was based on the average months working mostly from home between February through April 2020; the Wave 1 WFH measure was based on the average months working mostly from home in May and June 2020. The cut-offs were based on when most participants completed each wave of data collection.

Country and region of residence

Participants indicated their country and region of residence (corresponding to NUTS1 for all countries except France, where the level of aggregation is higher). During the observation period, a minority of participants temporarily resided in a different country (n = 2; 0.1%) or changed their region of residence (n = 284; 8.3%). We used participants' primary country and region of residence (i.e., mode country/region across all waves of participation). When region was multimodal, we used the most recent mode.

Stay-at-home restrictions

The relationship between WFH and well-being may be confounded by stay-at-home restrictions issued by the government during the pandemic. We therefore included *stay-at-home restrictions* as a time-varying covariate. We used daily, country-specific data from the Oxford COVID-19 Government Response Tracker (https://ourworldindata.org/covid-stay-home-restrictions) to calculate the average severity of government restrictions experienced by each participant for the same time frame covered by the WFH measure (e.g., the Wave 0 stay-at-home restrictions measure covered February 1 through April 30, 2020; the Wave 1 assessment covered May 1 through June 30, 2020). Stay-at-home restrictions was coded as 0 (*no restrictions*), 1 (*recommended not to leave the house*), 2 (*required not to leave the house with exceptions for daily exercise*, *grocery shopping and "essential" trips*) or 3 (*required to not leave the house with minimal exceptions*).

Sociodemographic characteristics

Participants answered single items regarding their age, gender (*female/male/other or prefer not to say*), highest level of educational attainment (*primary; general education (secondary) school; general certificate of secondary education (O-levels or equivalent); higher education entrance education (A-levels or equivalent); Vocational education/training; Bachelor's degree; Master's degree; Doctoral degree (PhD*, *MD*, *etc.); other*), relationship status (*single*, *never married; single*, *divorced or widowed; in a relationship/ married but living apart; in a relationship/married and cohabiting*), and number of children aged 0–4 and 5–12. We used the data to create dummy variables for *female* gender (yes = 1, no = 0); *tertiary degree* (yes = 1, no = 0; persons who answered "other" were treated as having missing data), primary *partner status* (yes = 1, no = 0) and *children* < *12* (yes = 1, no = 0). We used participants' primary statuses across the observation period as fixed covariates; when status was multimodal, we used the most recent mode.

Physical health

Physical health was assessed at Waves 0 through 3 and 8 through 10. Participants indicated whether they had any of the following conditions (yes = 1, no = 0): *high blood pressure*, *diabetes*, *heart disease*, *lung disease (e.g.*, *asthmas or COPD)*, *cancer*, *another clinically diagnosed chronic physical health condition*, *a disability that affects my ability to leave the house*, *any other disability*. Because most participants indicated having no conditions, we categorized individuals as either having 0 or 1 + physical conditions. We then calculated each participant's average *physical health* across the observation period.

Household income

Participants indicated their total monthly income considering all sources and all household members in EUR (*0–1 250; 1 250–2 000; 2 000–4 000; 4 000–6 000; 6 000–8 000; 8 000–12 500; >12 500; prefer not to say*). Using the midpoint of the income categories and purchasing power parity data from the OECD, responses were translated into the equivalent monthly net household income in purchasing power parity (with the equivalence scale being the square root of the family size) in 2019 United States dollars. Household income was assessed at each wave; we calculated each participant's average *household income* across the observation period.

Work characteristics

At each wave, participants indicated whether they were employed part-time ("part-time" was undefined; yes = 1, no = 0) as well as their occupational category (*legislators, senior officials and managers; professional; technicians and associate professionals; clerical support workers; service and sales workers; skilled agricultural, forestry and fishery workers; craft and related trades workers; plant and machine operators, and assemblers; elementary occupations; armed forces occupations*). We used the data to assess participant's average participation in *part-time work* and their primary *occupation* across the observation period. When occupation was multimodal, we used the most recent mode.

Statistical analysis

We used IBM SPSS Statistics 29 to conduct the preliminary and descriptive analyses. There was no missing data due to item non-response on country, region, life satisfaction, distress (or any of its three indicators), WFH, work characteristics, or stay-at-home restrictions. There was some missing data due to item non-response on children < 12 (0.1%), tertiary degree (0.4%), physical health (5.6%), and household income (3.8%). The amount of missing data due to item non-response was trivial and could be predicted by the available information with a reasonable degree of confidence (e.g., information on occupational category could be used to predict whether a participant had a tertiary degree). We therefore used the expectation-maximization imputation algorithm in SPSS to impute the missing values. The imputation model included country (entered as a series of dummy variables), age, female, part-time work, occupation (entered as a series of dummy variables), partner, child < 12, physical health, household income, personal average WFH, personal average life satisfaction, and personal average distress.

To assess whether working from home was related to life satisfaction and/or distress, we used HLM 8.2.3.14 (Scientific Software International, 2022) and a three-level multilevel (or hierarchical) regression model with wave (level 1; 11 waves; Z = 21,503 observations) nested within participants (level 2; N = 3403 participants) nested within regions (level 3; K = 39 regions). Traditional regression analysis requires independent observations. The current data had, however, two sources of non-independence (measurements within persons, and persons within the same country). Multilevel regression analysis appropriately accounts for the non-independence of our data and also makes it possible to disentangle within- from between-person relationships between WFH and well-being. For details on the use of multilevel regression analysis for longitudinal data, we refer to [39].

Wave was coded as 0 to 10, so that the intercept is the participant's level of the dependent variable at the first measurement point. We analyzed life satisfaction and distress separately. To be able to compare the size of the coefficients, we z-standardized life satisfaction prior to analysis (based on the sample of Z = 21,503 observations). As a factor score, distress was already standardized by default. In all models, country was entered as a series of dummy variables on level 3 (reference: Sweden, the only country in the sample which did not mandate persons to stay-at-home at any point during the pandemic). Unless otherwise noted, we interpreted the robust standard errors which are less sensitive to deviations from the model assumptions.

We first ran the empty models with random intercepts without and with the four country dummy variables on level 3 to calculate the intraclass correlation coefficients (i.e., the proportion of variance in the dependent variable associated with differences between waves, people, and regions). Based on the preliminary graphical analysis of the raw data and model comparisons, we then fit the average trajectory of life satisfaction and distress across waves. Preliminary inspection of the raw data suggested that both life satisfaction and distress initially improved between Waves 0 and 2, was worse at Waves 3 and 4, and then improved again in Wave 5 onwards. The general pattern suggested that the average trajectories could best be described with three piecemeal growth terms. We used the significance of the coefficients and the change in model fit (i.e., change in deviance and chi-square tests) to determine satisfactory models of the average trajectories, and whether specifying random as opposed to fixed growth terms improved model fit. Our aim was to identify the simplest trajectory that fit the data reasonably well.

Once we had satisfactorily modeled the average trajectories, we ran a first model including the growth terms on level 1 and the country dummies on level 3 (Model 1). We then added the intensity of WFH as a time-varying covariate with group mean centering on level 1, and personal average intensity of WFH with grand mean centering as a predictor of the intercept and growth terms on level 2 (Model 2). Both variables were entered as fixed effects. This allowed us to disentangle the within-person from the between-person relationship between WFH and well-being. In other words, we were able to simultaneously examine whether WFH more or less than one usually worked from home was associated with having higher or lower life satisfaction/distress than one's usual level of life satisfaction/distress (i.e., the extent to which wave-to-wave fluctuations in WFH were related to wave-to-wave fluctuations in well-being), as well as whether people who generally worked at home more/less than other people had higher/lower baseline values and/or different patterns of change in well-being (i.e., the extent to which between-person differences in WFH were related to between-person differences in well-being; see also [40]).

We then added the level 1 and level 2 control variables to the model. Specifically, we controlled for stay-at-home restrictions as a time-varying covariate on level 1 (uncentered) and for participants' age, female gender, tertiary degree, health, household income (standardized), partner, child < 12, and occupation (entered as a series of dummy variables; reference: clerical support workers as the most frequent category) on level 2 (Model 3). The control variables were entered as predictors of the intercept as well as the change terms. Continuous level 2 variables were grand-mean centered; dummy variables were uncentered. All control variables were entered as fixed effects. We examined histograms of the level 1 residuals of to confirm that the residuals were normally distributed.

Robustness check: predictors and effects of participation intensity

To better understand how participation bias (i.e., the tendency of people with particular characteristics to drop out of the study or participate less frequently) may have affected our results, we first used a negative binomial regression model (appropriate for dependent variables which are over dispersed) to examine how the study variables were related to participation intensity. Participation intensity was the dependent variable. We included country (entered as a series of dummy variables), age, female gender, tertiary degree, partner, child < 12, physical health, household income (standardized), part-time work, occupation (entered as a series of dummy variables), personal average intensity of WFH, personal average life satisfaction, and personal average distress as predictors. We also re-ran the multilevel analyses of life satisfaction and distress after adding participation intensity as an additional statistical control to Model 3.

Results

Across all waves of observations, the intensity of WFH was $M = 0.25$ ($SD = 0.39$). Figure 1 displays the intensity of WFH at each wave, overall and in each country.

The results of the empty model indicated that most of the variance in life satisfaction and distress was explained by differences between participants (55.8% for life satisfaction; 66.8% for distress) and waves (43.8% for life satisfaction; 30.4% for distress). Hardly any variance was explained by differences between regions (0.4% for life satisfaction, 2.8% for distress); there was no variance associated with region after statistically controlling for country.

For life satisfaction, the average trajectory was described by a linear increase between Waves 0 to 2, a constant term for Waves 3 and 4, and a separate constant term for Waves 5 through 10. For distress, the average trajectory was described by a linear decrease between Waves 0 to 2, a constant term for Waves 3 and 4 (which did not significantly differ from distress at baseline, p =.054) and a separate constant term for Waves 5 through 10. All piecemeal change terms were specified as random. A graphical comparison of the raw data and the modelled average trajectories, as well as a graphical depiction of the trajectories of $n = 15$ randomly selected participants, are available in the Supplementary material (see Figures A1 and A2).

The full results of the multilevel regression analyses are available in the Supplementary material (see Tables A3 and A4). The results from Models 2 (no statistical controls) and 3 (with statistical controls) were highly similar; below, we refer to the results of Model 3. The multilevel regression analyses revealed no evidence that intraindividual (i.e., within-person) differences in WFH were associated with intraindividual differences in either life satisfaction (B = 0.01, SE = 0.02, t(7850) = 0.51, p =.61) or distress (B=-0.03, SE = 0.02, t(7850)=-1.77, p =.08). In other words, there was no evidence that WFH more or less than usual during the observation period was associated with being more or less satisfied/distressed than usual. There was also no evidence that interindividual (i.e., between-person) differences in working from home were associated with interindividual differences in life satisfaction at baseline (April/May 2020), B=-0.06, SE = 0.06, t(3289)=-1.08, p =.28. However, participants who typically worked at home more often during the observation period were more distressed at baseline than people who worked at home less during the observation period, B = 0.13, SE = 0.05, t(3289)=-2.53, p =.01. Between

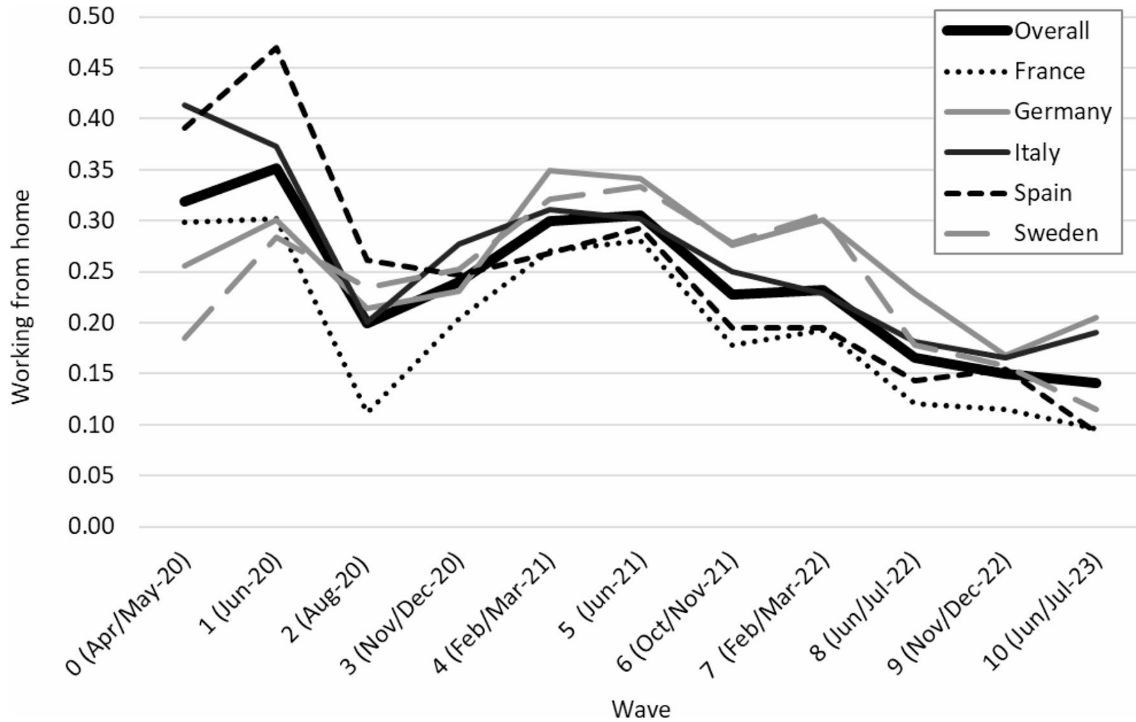

Fig. 1 Intensity of working from home at each wave, overall and in each country

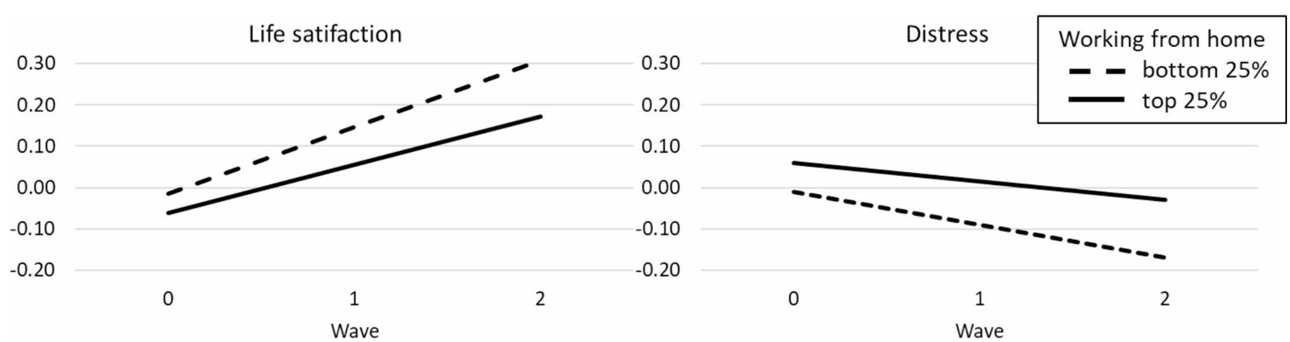

Fig. 2 Participants who worked from home less often experienced a stronger increase in life satisfaction and a stronger decline in distress between Waves 0 and 2. Graphs based on Model 3

Waves 0 and 2, people who worked from home *less* often experienced a stronger increase in life satisfaction (B=-0.10, SE = 0.03, t(3289)=-3.20, p =.001) and a stronger decline in distress (B = 0.07, SE = 0.03, t(3289) = 2.82, p =.01; please note that p =.08 in Model 2 without statistical controls) (see Fig. 2). There was no evidence that patterns of either life satisfaction or distress between Waves 3–4 or Waves 5–10 were related to how much participants worked from home (all p >.13).

Robustness check: participation intensity

Higher distress, country, female gender, younger age, lower household income, not having a partner, not having children under 12, and working part-time were related to *lower* participation intensity. Participation intensity was also related to participants' occupation. There was no indication that participation intensity was associated with having a tertiary degree, physical health, participants' average intensity of WFH across the observation period, or participants' average life satisfaction across the observation period. The full results of the negative binomial regression are in the Supplementary material (see Table A5). Including participation intensity as an additional statistical control did not meaningfully change any of the results regarding the relationship between working from home and either life satisfaction or distress (see Table A6).

Discussion

The increase in WFH stimulated by the COVID-19 pandemic has heightened the urgency of understanding its association with well-being. So far, evidence from the extensive literature on the relationship between WFH and well-being has been mixed. In the current study, we added to the discussion by analyzing dense, longitudinal data on WFH and well-being from a large population-based sample of adults in five European countries over the course of three years during and beyond the pandemic. Our analysis therefore offers a differentiated picture on within- and between-person dynamics. Our results can inform discussion of the impact of government measures during the pandemic on the population, as well as how individuals, organizations, and societies can prepare for a future in which WFH plays a more prominent role.

Our findings show that, even when controlling for a large number of relevant covariates, WFH was negatively related to well-being in the initial stages of the pandemic: Between Waves 0 and 2 (April to August 2020), people who worked from home less often experienced a stronger increase in life satisfaction and a stronger decline in distress. In other words, people who worked from home less often seem to have adapted to the pandemic situation more quickly. This may be because their usual day-to-day lives were less disrupted by the pandemic relative to participants who worked at home more often. Furthermore, the lag in access to appropriate equipment and technical support for remote work, as well as additional care duties for participants with families, might have negatively impacted well-being for those working mostly from home at the earlier stages of the pandemic.

After these first pandemic months, however, there was no evidence that WFH was related to either life satisfaction or psychological distress at the population level. As the pandemic progressed, companies set up the ergonomical and technical prerequisites for WFH and schools reopened, which might have mitigated the negative early effect of WFH. Furthermore, especially in the beginning of the pandemic, WFH was largely mandatory. Post-pandemic, however, it seems likely that how often one works from home is more related to how often one *prefers* to work from home, which might increase perceived autonomy and reduce any negative effects [26, 40].

The lack of evidence regarding an average relationship between WFH and well-being should not be mistaken, however, as evidence that WFH and well-being are per se unrelated. Our study focused on the overall, dynamic association between WFH and two indicators of well-being, and our analyses do not provide any insight about moderating factors or mediating processes. WFH may well be related to well-being under particular conditions or for particular persons. Previous research has suggested that the relationship between WFH and well-being may depend on moderating factors such as organizational support, leadership behavior, job characteristics, personal preferences, and the possibility to set boundaries between work and private life [41]. Moreover, WFH might trigger a number of mediating processes (e.g., coping, self-regulation) that could nevertheless result in a null relationship between WFH and well-being. We suspect that the influence of any moderators and mediating processes may also depend on the time-point of investigation (e.g., pre-pandemic, during the lockdowns, post-pandemic). For instance, Leitner [15] found that work-family conflict and family-work conflict were only relevant mediators of the relationship between WFH and well-being at the beginning of the pandemic. Future studies should investigate mediators and moderators of inter- and intraindividual associations of WFH and different indicators of well-being.

Notably, irrespective of WFH, average life satisfaction and distress were highly stable during the observation period, varying only between −0.15 and +0.15 standard deviations around the mean of all observations. Indeed, variance in both measures of well-being during the observation period was more closely associated with between-person, trait-like differences than to within-person, wave-to-wave fluctuations. Given that our observation period covered the height of the COVID-19 pandemic as well as its aftermath, the overall stability of life satisfaction and distress is remarkable. We interpret the overall stability of well-being at the population level as evidence that people actively and passively regulate their well-being, even in the most difficult of circumstances. The human ability to maintain stability in well-being has been discussed previously in terms of psychological resilience (e.g [42]), or the fluctuation of well-being around a (biological) set-point (e.g [43]). Both approaches, however, have been criticized theoretically and methodologically. Notably, in our study there were large differences in the dynamics of life satisfaction and distress between individuals (see Figure A3), which warrant further study in both work and non-work-related contexts [32].

Our study has several strengths, including its large, diverse, population-based sample from different countries; the high density of assessments; high participation intensity (the vast majority of participants took part in at least four waves); the high number of considered covariates, including the severity of stay-at-home restrictions; the multidimensional assessment of well-being; and the decomposition of the within- and between-person components of the relationship between WFH and well-being. Several limitations must be noted, however. Our assessment started after the pandemic had already begun, which does not allow us to contrast pre- with during and post-pandemic dynamics. While our sample was representative in terms of gender and region, the online mode of data collection might have limited the representativeness of our sample with regard to other characteristics, such as age. Our correlational design does not allow us to draw causal conclusions about the direction of the relationship between WFH and well-being. It is plausible that WFH affects well-being, and also that well-being affects how often people work from home. Moreover, our results may be explained by unmeasured confounders. In addition, our measure of WFH was rather rough. Given recent findings on the non-linear relation of WFH and several outcomes [8], a more differentiated measure of WFH (e.g., the precise number of days one worked from home) might have yielded different results. Furthermore, nearly half (52.8%) of participants changed occupational categories over the course of the study; we were, however, unable to account for occupational change as a time-varying covariate on level 1 because we were unable to identify when exactly the occupational change occurred. We did not examine moderators or mediators of the WFH and well-being relationship due to data restrictions and to keep the complexity of the analyses within reasonable bounds. Future studies on the dynamic relationship between WFH and well-being should consider including dynamic assessments of control variables as well as potential moderators and mediators.

Finally, we note that some participants took part in more waves than others, and we had high, unexplained dropout in Wave 10 (participation increased again in subsequent waves of the study that were unavailable at the time of writing, so it is likely that the high dropout in Wave 10 was due to a technical issue). An important advantage of multilevel analysis is that it takes all available observations into account, and there is no need for all participants to have the same number of observations or for observations to be equally spaced. We also found no evidence that controlling for participation intensity meaningfully affected our results. Nevertheless, we caution that the less frequent participation of persons with higher distress, female gender, younger age, lower household income, without a partner, without children under 12, from some countries and those working part-time may have affected some of our results. In particular, we caution that the raw averages of intensity of WFH by country (Fig. 1) may be biased.

Conclusions

The pandemic has accelerated the dissolution of the traditional workplace, profoundly changing how, when and where people work [5]. The increase in WFH has prompted legislators to address how structural and legislative measures can protect the population's well-being as working conditions change [7, 44]. A better understanding of how WFH is related to different dimensions of well-being, as delivered in the present study, could inform policy decisions.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12889-025-22349-4.

Supplementary Material 1

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Not applicable.

Author contributions

All authors contributed to the conceptualization of the research question. CV, CDA, AK and LR secured the funding. AL was responsible for data curation. CB performed statistical analyses. AK wrote the first draft of the introduction and discussion section. CB wrote the first draft of the methods and results section and produced tables and figures. All authors reviewed the manuscript and provided feedback.

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Data availability

The COME-HERE data contain sensitive individual information and cannot be made publicly available (Ethics Research Panel of the University of Luxembourg, decision number erp 20-026 c/a come-here). Data access on the University of Luxembourg server can be obtained to reproduce the present analyses by contacting the Department of Behavioral and Cognitive Sciences (dbcs.secretariat@uni.lu) or the corresponding author (anna.kornadt@uni.lu). Statistical code and results are made available nevertheless to allow for transparency and comprehend the performed analyses and results. SPSS syntax file was used to create the various data sets used in the current study, as well as the commands for the statistical analyses. The analyses required the creation of a simplified data file including only those variables relevant for the current study; a restructured data file; the creation of an Excel file for identifying the mode of various level 2 (i.e., person-level) characteristics, region and country; and separate data files describing the level 1 data (observations), the level 2 data (participants) and the level 3 data (regions). HLM files include command files and results of the multilevel analyses conducted using HLM. We furthermore uploaded the information regarding the stay-at-home-restrictions used in our paper. All files are available at the Open Science Framework https://osf.io/k3fvr/?view_only=cbee2a22a09e4f47b44c7756b93134e0.

Declarations

Ethics approval and consent to participate

COME-HERE was approved by the Ethics Research Panel of the University of Luxembourg, decision number erp 20–026 c/a come-here. We confirm that all research was performed in accordance with the relevant guidelines and regulations. Participants provided informed consent before they were sent the survey link.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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References

1. Christensen JO, Finne LB, Garde AH, Nielsen MB, Sørensen K, Vleeshouwers J. The influence of digitalization and new technologies on psychosocial work environment and employee health: a literature review. Statens Arbeidsmiljøinstitutt, Nationalt Forskningscenter for Arbejdsmiljø; 2020. Available from: https://stami.brage.unit.no/stami-xmlui/handle/11250/2723779
2. Gajendran RS, Harrison DA. The good, the bad, and the unknown about telecommuting: Meta-analysis of psychological mediators and individual consequences. J Appl Psychol. 2007;92(6):1524–41. Available from: https://doi.org/10.1037/0021-9010.92.6.1524
3. Eurofound. Telework in the EU: Regulatory frameworks and recent updates. Luxembourg: publications office of the european union. 2022. Available from: https://data.europa.eu/doi/10.2806/42974
4. Eurofound. The rise in telework: impact on working conditions and regulations. luxembourg: publications office of the european union. 2022. Available from: https://eurofound.link/ef22005
5. Leonardi PM, Parker SH, Shen R. How remote work changes the world of work. annu rev organ psychol organ behav. 2024;11(1):193–219. Available from: https://doi.org/10.1146/annurev-orgpsych-091922-015852
6. Marsh E, Vallejos EP, Spence A. The digital workplace and its dark side: An integrative review. Comput Human Behav. 2022;128:107118. Available from: https://doi.org/10.1016/j.chb.2021.107118
7. Ratti L, Potocka-Sionek N, Kornadt AE, Vögele C. Workplace reloaded. How the 'worksphere' challenges the promotion of well-being at work. [submitted].
8. Rudolph CW, Zacher H. Working from home: When is it too much of a good thing? Hum Resour Dev Q. 2024. Available from: https://doi.org/10.1002/hrdq.21530
9. Kniffin KM, Narayanan J, Anseel F, Antonakis J, Ashford SP, Bakker AB et al. COVID-19 and the workplace: Implications, issues, and insights for future research and action. Am Psychol. 2021;76(1):63–77. Available from: https://doi.org/10.1037/amp0000716
10. Senik C, Clark AE, d'Ambrosio C, Lepinteur A, Schröder C. Teleworking and life satisfaction during COVID-19: the importance of family structure. J Popul Econ. 2024;37(1):8.
11. Hill NS, Axtell C, Raghuram S, Nurmi N. Unpacking virtual work's dual effects on employee well-being: An integrative review and future research agenda. J Manag. 2024;50(2):752–92. Available from: https://doi.org/10.1177/01492063221131535
12. Charalampous M, Grant CA, Tramontano C, Michailidis E. Systematically reviewing remote e-workers' well-being at work: a multidimensional approach. Eur J Work Organ Psychol. 2018;28(1):51–73. Available from: https://doi.org/10.1080/1359432x.2018.1541886
13. Gualano MR, Santoro PE, Borrelli I, Rossi MF, Amantea C, Daniele A et al. TEleWoRk-RelAted Stress (TERRA), psychological and physical strain of working from home during the COVID-19 pandemic: A systematic review. Workplace health Saf. 2023;71(2):58–67. Available from: https://doi.org/10.1177/21650799221119155
14. Hall CE, Davidson L, Brooks SK, Greenberg N, Weston D. The relationship between homeworking during COVID-19 and both, mental health, and productivity: a systematic review. BMC Psychol. 2023;11(1). Available from: https://doi.org/10.1186/s40359-023-01221-3
15. Leitner SM. Working from home and mental well-being at different stages of the COVID-19 pandemic. PLoS ONE. 2024;19(11):e0312299. Available from: https://doi.org/10.1371/journal.pone.0312299
16. Lunde L, Fløvik L, Christensen JO, Johannessen HA, Finne LB, Jørgensen IL et al. The relationship between telework from home and employee health: a systematic review. BMC public health. 2022;22(1). Available from: https://doi.org/10.1186/s12889-021-12481-2
17. Oakman J, Kinsman N, Stuckey R, Graham M, Weale V. A rapid review of mental and physical health effects of working at home: how do we optimise health? BMC Public Health. 2020;20(1):1825. Available from: https://doi.org/10.1186/s12889-020-09875-z
18. Denzer M, Grunau P. The impacts of working from home on individual health and well-being. Eur J Health Econ. 2023;25(5):743–62. Available from: https://doi.org/10.1007/s10198-023-01620-8
19. Yang D, Kelly EL, Kubzansky LD, Berkman L. Working from home and worker well-being: new evidence from germany. ilr rev. 2023;76(3):504–31. Available from: https://doi.org/10.1177/00197939221148716
20. Zhang C, Yu MC, Marin S. Exploring public sentiment on enforced remote work during COVID-19. J Appl Psychol. 2021;106(6):797–810. Available from: https://doi.org/10.1037/apl0000933
21. Seeber I, Erhardt J. Working from home with flexible and permeable boundaries. bus inf Syst Eng. 2023;65(3):277–92. Available from: https://doi.org/10.1007/s12599-023-00801-2
22. Sonnentag S, Tay L, Nesher Shoshan H. A review on health and well-being at work: More than stressors and strains. Pers Psychol. 2023;76(2):473–510. Available from: https://doi.org/10.1111/peps.12572
23. Green N, Tappin D, Bentley T. Working from home before, during and after the Covid-19 pandemic: implications for workers and organisations. N Z J Employ Relat. 2020;45(2):5–16. Available from: https://doi.org/10.24135/nzjer.v45i2.19
24. Bilgrami A. Working from home and mental health: Before and during the COVID-19 pandemic (No. 1265). GLO discussion paper. 2023. Available from: https://doi.org/10.2139/ssrn.4411790
25. Carillo K, Cachat-Rosset G, Marsan J, Saba T, Klarsfeld A. Adjusting to epidemic-induced telework: empirical insights from teleworkers in France. Eur J Inf Syst. 2020;30(1):69–88. Available from: https://doi.org/10.1080/0960085x.2020.1829512
26. Kaluza AJ, Van Dick R. Telework at times of a pandemic: The role of voluntariness in the perception of disadvantages of telework. curr psychol. 2022;42(22):18578–89. Available from: https://doi.org/10.1007/s12144-022-03047-5
27. Elbaz S, Richards JB, Provost Savard Y. Teleworking and work–life balance during the COVID-19 pandemic: A scoping review. can psychol. 2023;64(4):227–58. Available from: https://doi.org/10.1037/cap0000330
28. Schifano S, Clark AE, Greiff S, Vögele C, D'Ambrosio C. Well-being and working from home during COVID-19. Inf technol people. 2023;36(5):1851-69. Available from: https://doi.org/10.1108/ITP-01-2021-0033
29. Lengen JC, Kordsmeyer A, Rohwer E, Harth V, Mache S. Soziale Isolation im Homeoffice im Kontext der COVID-19-Pandemie. zentralbl arbeitsmed arbeitsschutz ergon. 2020;71(2):63–8. Available from: https://doi.org/10.1007/s40664-020-00410-w
30. Zhang P, Chen S. Association between workplace and mental health and its mechanisms during COVID-19 pandemic: A cross-sectional, population-based, multi-country study. J Affect Disord. 2022;310:116– 22. Available from: https://doi.org/10.1016/j.jad.2022.05.038
31. Wels J, Wielgoszewska B, Moltrecht B, Booth C, Green MJ, Hamilton OK et al. Home working and social and mental wellbeing at different stages of the COVID-19 pandemic in the UK: Evidence from 7 longitudinal population surveys. PLoS Med. 2023;20(4):e1004214. Available from: https://doi.org/10.1371/journal.pmed.1004214
32. Sonnentag S. Dynamics of Well-Being. annu rev organ psychol organ behav. 2015;2(1):261–93. Available from: https://doi.org/10.1146/annurev-orgpsych-032414-111347
33. Vögele C. Health and Well-being from a Psychological Perspective. In: Springer eBooks; 2022. pp. 11–26. Available from: https://doi.org/10.1007/978-3-658-35744-3_2
34. Vögele C, Lutz A, Yin R, D'Ambrosio C. How do different confinement measures affect people in Luxembourg, France, Germany, Italy, Spain and Sweden? First COME-HERE Report. Available from: https://osf.io/k3fvr/?view_only=cbee2a22a09e4f47b44c7756b93134e0
35. Database. 2020. Available from: https://ec.europa.eu/eurostat/databrowser/explore/all/all_themes?lang=en%26display=list%26sort=category
36. Spitzer RL, Kroenke K, Williams JB, Löwe B. A brief measure for assessing generalized anxiety disorder: The GAD-7. Arch Intern Med. 2006;166(10):1092–7. Available from: https://doi.org/10.1001/archinte.166.10.1092
37. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: Validity of a brief depression severity measure. J Gen Intern Med. 2001;16(9):606–13. Available from: https://doi.org/10.1046/j.1525-1497.2001.016009606.x
38. Cohen S, Kamarck T, Mermelstein R. A global measure of perceived stress. J Health Soc Behav. 1983;24(4):385. Available from: https://doi.org/10.2307/2136404
39. Hoffman L. Longitudinal Analysis. 1st ed. Routledge; 2015. Available from: https://doi.org/10.4324/9781315744094
40. Heiden M, Hallman DM, Svensson M, Mathiassen SE, Svensson S, Bergström G. mismatch between actual and preferred extent of telework: cross-sectional and prospective associations with well-being and burnout. BMC Public Health. 2023;23(1). Available from: https://doi.org/10.1186/s12889-023-16683-8
41. Gohoungodji P, N'Dri AB, Matos ALB. What makes telework work? Evidence of success factors across two decades of empirical research: a systematic and critical review. Int J Hum Resour Manag. 2022;34(3):605– 49. Available from: https://doi.org/10.1080/09585192.2022.2112259

42. Fletcher D, Sarkar M. Psychological resilience: A review and critique of definitions, concepts, and theory. Eur Psychol. 2013;18(1):12–23. Available from: https://doi.org/10.1027/1016-9040/a000124
43. Lucas RE. Adaptation and the set-point model of subjective well-being: Does happiness change after major life events? Curr Dir Psychol Sci. 2007;16(2):75–9. Available from: https://doi.org/10.1111/j.1467-8721.2007.00479.x
44. Ratti L, Garcia-Munoz A. The regulation of remote work. Seeking balance through the articulation of labour law Sources – A comparative appraisal. Int J Comp Labour Law Ind Relat. 2024;40(3).

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