



Germany's capacity to work from home

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ABSTRACT

We propose an index of working from home (WFH) capacity for the German economy, drawing on rich survey and administrative data. We find that 56 percent of jobs are WFH feasible, most of which are located in urban areas and in highly digitized industries. Using individual-level data on tasks and work conditions, we show that heterogeneity in WFH feasibility is largely explained by differences in task content. WFH feasible jobs are typically characterized by cognitive, non-manual tasks, and PC usage. We compare our survey-based measure with popular task-based measures of WFH capacity, which usually rely on determining tasks that are incompatible with WFH, and show that task-based approaches capture variation in WFH capacity across occupations fairly accurately. A simple measure of PC use intensity will generally constitute a suitable proxy for WFH capacity. Finally, we demonstrate that our WFH index is a strong predictor of actual WFH outcomes during the Covid-19 crisis and discuss applications in the context of the pandemic and the future of work.

1. Introduction

In the wake of the Covid-19 pandemic and the associated containment measures, working from home (WFH) has experienced an unprecedented boom. Survey evidence suggests that 42 (Bloom, 2020) to 50 percent (Brynjolfsson et al., 2020) of U.S. workers worked from home during April and May 2020.² Similar shifts are recorded in Europe, with nearly 60 percent of workers in Finland and the Netherlands switching to WFH due to the crisis and close to 40 percent in Germany (Eurofound, 2020). Around the globe, WFH constituted a central measure to reduce physical proximity among workers, while maintaining economic activity. At the same time, the transition to WFH is likely to permanently change the organization of work for several reasons: First, companies that switched to WFH incurred fixed costs from digitizing work processes, upgrading IT infrastructure, implementing digital communication tools, and training employees in their usage (Barrero et al., 2021). Second, evidence shows that WFH policies

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² Bick et al. (2021, Fig. 1) report a 44.8 percent WFH share for May 2020.

can represent a competitive advantage in attracting qualified labor (Mas and Pallais, 2017; Barrero et al., 2021) and generate sizeable productivity gains when implemented (Angelici and Profeta, 2020; Bloom et al., 2014; Choudhury et al., 2021; Harrington and Emanuel, 2021). Thus, once fixed costs are borne and WFH stigma lifted, a permanent expansion of WFH relative to the pre-crisis level is plausible. This raises two interrelated questions: How many and what type of jobs can be done from home?

We estimate the German economy's overall capacity to work from home and present a WFH capacity index for occupations, industries, and regions. Our analysis draws on administrative employment statistics and individual-level information from the 2018 BIBB/BAuA Employment Survey. The dataset covers more than 17,000 employees and includes information on pre-pandemic WFH take-up and individual WFH feasibility as well as the task content of jobs. Unlike task-based measures popularized by Dingel and Neiman, (2020), hereinafter *DN*, our WFH index is based on the self-assessment of employees and is thus independent of plausibility judgments about the compatibility of tasks with WFH.³ Moreover, rather than employing US estimates of occupation task content, we use country-specific data to provide an accurate account of feasibility constraints of WFH in the German economy.⁴

We find that a total of 56 percent of jobs can be done from home. WFH feasible jobs are typically located in urban, densely populated areas, and in highly digitized industries. Importantly, unlike most previous studies, our measure is not limited to jobs that can be done from home *entirely* but also includes partial WFH. Including partial WFH feasible jobs captures feasibility constraints and thus the potential to maintain social distance at work more accurately (Adams-Prassl et al., 2022; Bick et al., 2021).⁵ Therefore, our measure provides a useful benchmark to evaluate or design policies aimed at containing Covid-19. We show that estimated WFH capacity is highly predictive of WFH outcomes during the pandemic and present further applications of our measure, such as analyzing the role of WFH in reducing infection risk and mitigating the economic shock of the pandemic in Germany.

Besides data on WFH feasibility, the BIBB/BAuA Survey also includes detailed information on the task content of jobs. A key novelty of our paper is that we can use this information to link heterogeneity in WFH feasibility to differences in task profiles at the individual job level and thus identify single tasks and work conditions that are most (or least) conducive to WFH. We show that a job's task content is an important determinant of WFH feasibility and find that the significance of background characteristics (e.g., gender) substantially declines once accounting for task profiles. WFH feasible jobs typically require more cognitive, non-manual tasks, and in particular the use of a computer. The results further contribute to understanding within- and across-occupation heterogeneity in terms of WFH feasibility documented in the literature (Adams-Prassl et al., 2022; Gottlieb et al., 2021) and with respect to occupational task content in general (Autor and Handel, 2013; Lewandowski et al., 2022).

Drawing on our findings, we compare employees' self-assessment of WFH feasibility with alternative task-based measures in the spirit of *DN*, which usually rely on determining tasks that are incompatible with WFH. We show that task-based measures perform well in capturing differences in WFH capacity across occupations. In settings with limited information on self-reported WFH or job tasks, a simple measure of PC use intensity will generally provide a suitable proxy of WFH capacity.

About half of the employees who could work from home did not do so prior to the pandemic. Most of this untapped capacity was due to employer-side rather than employee-side restrictions. We analyze the selection into actual WFH conditional on WFH feasibility and show that individuals with lower levels of education and income were less likely to realize WFH opportunities. We discuss an application of our measure of untapped WFH capacity, showing that during the pandemic, employers' WFH offers increased most in occupations with previously larger unused potentials. As such, our measure also provides a suitable input to models used to analyze the spatial division and the organization of work in the post-pandemic era.⁶

In Section 2, we describe how we construct our WFH capacity index and discuss alternative approaches in the literature. In Section 3, we present evidence of heterogeneity in WFH capacity across occupations and analyze the determinants of WFH feasibility and untapped WFH at the individual level. We further present the geographical and industry-level distribution of WFH capacity. Section 4 is dedicated to WFH in the context of the Covid-19 pandemic. We test how well our measure predicts WFH outcomes during the pandemic and discuss applications of our WFH measures. In Section 5, we compare our survey-based measures of WFH capacity with alternative task-based measures. Section 6 concludes.

2. Measuring WFH capacity

2.1. Approaches to measuring WFH capacity in the literature

Our paper relates to a recent strand of research aimed at quantifying WFH capacities, i.e., how many jobs can potentially be done from home. In their influential paper, *DN* determine job characteristics that arguably *preclude* the possibility of entirely working from home (e.g., working outdoors) based on O*NET task data and classify occupations as either compatible or incompatible with WFH. Combining the classification with the prevalence of each occupation in the economy, the authors find that a maximum of 37 percent of U.S. jobs can entirely be performed from home. This task-exclusion approach to measure WFH capacity has become very popular.

³ Specifically, *DN* propose a task exclusion approach to measure WFH capacity, which involves defining a set of tasks or work conditions that cannot be performed at home.

⁴ E.g., Gottlieb et al. (2021) and Lewandowski et al. (2022) demonstrate that cross-country differences in task content within the same occupations are sizeable.

⁵ Focusing only on jobs that can be performed from home entirely tends to underestimate actual capacities in the economy, as evidence on actual WFH rates during the Covid-19 lockdown shows (Brynjolfsson et al., 2020, 2022).

⁶ All measures are available for download at the occupation level (2-digit and 3-digit KldB-2010 and ISCO-2008 occupations), the industry level (88 2-digit NACE industries), and the county level (401 NUTS-3 level regions) at: https://github.com/jvali1/alipouretal_wfh_germany/tree/master

Several studies have proposed variants of this method and applied them numerous countries.⁷ Estimates for the German economy vary widely, including 17 (Pestel, 2020), 29 (Boeri et al., 2020), 37 (DN, 2020) 42 percent (Fadinger and Schymik, 2020). The range of estimates is sizeable, reflecting different judgments about which job characteristics are incompatible with WFH as well as different data limitations.

A common theme of these studies is the focus on jobs that can potentially be performed *entirely* at home. We argue that excluding jobs in which only part of work can be carried out at home might miss important adjustments in the economy for several reasons: First, recent survey evidence indicates that most workers can do some (rather than all or none) of their job tasks at home (Adams-Prassl et al., 2022). This finding is also in line with the observation that full-time WFH rates before the pandemic were typically low, e.g., 3.5 percent in Germany (BIBB/BAuA Survey 2018), 5.1 percent in the U.K. Watson (2020), and around 4 percent in the U.S. Mas and Pallais (2020, Fig. 1). Second, evidence suggests that partial WFH has both contributed to maintaining economic activity (measured via the likelihood of job loss or short-time work) and mitigating the spread of Covid-19 (Adams-Prassl et al., 2020; Alipour et al., 2021a; Bick et al., 2021). This is corroborated by the fact that measures of full-time WFH capacity have underestimated actual WFH rates during the pandemic lockdown (see Brynjolfsson et al., 2020 for this observation in the U.S. context). Hence, the pandemic-related WFH shock and its ramifications for the economy are not solely driven by the subset of employees with full-time WFH feasible jobs, but also include those who can do partial WFH. A policy-relevant measure of WFH capacity should therefore account for both types of jobs.

Another set of studies draws on pre-pandemic employment surveys in which individuals directly report their WFH practices to measure WFH capacity—see e.g., Alon et al. (2020), Hensvik et al. (2020) and Papanikolaou and Schmidt (2022) using the American Time Use Survey. An advantage of this approach is that assessments of job suitability for WFH are independent of researchers' own judgments. A drawback is that most pre-pandemic surveys inquire about actual WFH prevalence rather than feasibility.⁸⁹ During the pandemic, the focus of surveys has shifted toward the latter. For instance, Adams-Prassl et al. (2022) surveyed about 25,000 U.S. and U.K. employees in April and May 2020 about the fraction of job tasks they can perform at home and document sizeable variation within occupations.

2.2. A new survey-based approach

Our approach leverages information from a nationally-representative survey for Germany, in which employees are asked about WFH feasibility, regardless of whether the employer actually offers WFH. We draw on information from 17,160 employees (aged 18–65, excluding the marginally employed) from the 2018 wave of the BIBB/BAuA Employment Survey (Hall et al., 2020).¹⁰ The survey elicits information on (pre-pandemic) actual WFH and, importantly, asks employees (who never work from home) about the *possibility* of working at home, specifically: “If your company would allow you to work at home temporarily, would you accept this offer?”—Yes; No; Is not possible with my work. We define a job as *WFH feasible* if the respondent does not rule out the possibility of WFH at her job or if she reports ever working from home.¹¹ Thus, our binary measure captures the full range of WFH feasibility, including jobs suitable for full or partial relocation to the home office. It is worth noting that an individual reporting that WFH is “not possible” does not necessarily correspond to 0 percent WFH feasible tasks as measured by Adams-Prassl et al. (2022), who elicit WFH feasibility on a continuous scale. It is likely that our measure additionally includes a judgment by employees as to what fraction of WFH feasible tasks makes WFH meaningfully possible in their job. Importantly, a measure of WFH feasibility should capture which jobs *can* be performed from home, i.e., whether WFH is technologically feasible, independent of worker characteristics. We show in Section 3.2 that individual-level variation in our measure is indeed largely explained by differences in job tasks and work conditions. We use the term *WFH capacity* to refer to the aggregate of WFH feasible jobs in an occupation, a region, or an industry. In the overall economy, 56 percent of jobs are WFH feasible. We break down actual WFH rates (pre-pandemic) by frequent and occasional WFH. Employees reporting ever working from home did so on average 6.6 h a week (median = 4 h), distributed across 2.6 weekdays (median = 2 weekdays). Table 1 presents our terminology and the survey questions used in this context.

Furthermore, using the information on employees' pre-pandemic WFH take-up, we can assess the level of *untapped WFH capacity*, defined as the fraction of employees never working from home despite having a WFH feasible job. Untapped capacities represent a useful metric to gauge the scope for increases in WFH usage at the extensive margin during and beyond the pandemic. In principle, untapped capacities can be due to limitations on the employer side (e.g., lacking infrastructure, no WFH policies) or on the employee side (e.g., personal preference for working from business premises, poor working conditions at home). We broadly categorize untapped capacities using the information on whether employees with a WFH feasible job would accept or decline their employer's offer to WFH. We assume that employees who would accept the offer face practical constraints from their employer (employer-side restrictions), while those who would reject the offer have no desire to WFH (employee-side restrictions). We discuss employer-side and employee-side restrictions in Section 3.3.

⁷ See e.g., Barbieri et al. (2022), Boeri et al. (2020), Del Rio-Chanona et al. (2020), Fadinger and Schymik (2020), Gottlieb et al. (2021), Holgersen et al. (2021), Mongey et al. (2021), OECD (2020), Pestel (2020) or Yasenov (2020).

⁸ In the American Time Use Survey (ATUS), respondents are asked “As part of your (main) job, can you work at home?”, which still conveys employer-side restrictions.

⁹ A notable exception is Mas and Pallais (2020) who employ questions about the fraction of work a respondent can do from home (module 82 of the 2017 Understanding America Survey). However, the sample size ($N = 625$) is relatively low to draw meaningful conclusions about occupational, sectoral, or regional distributions of WFH feasibility.

¹⁰ BIBB: Federal Institute for Vocational Education and Training (Bundesinstitut für Berufsbildung); BAuA: Federal Institute for Occupational Safety and Health (Bundesanstalt für Arbeitsschutz und Arbeitsmedizin).

¹¹ See Mergener (2020) and Brenke (2016) for similar definitions of WFH feasibility at the employee level.

Table 1
Terminology & survey questions.

Survey question		Answer categories
[A]	“Do you work for your company (even if only occasionally) from home?”	Yes; No.
[B]	“How frequently [do you work from home]?”	always; frequently; sometimes; rarely.
[C]	“If your company would allow you to work at home temporarily, would you accept this offer?”	Yes; No; Is not possible with my work.
Term	Definition	Level
actual WFH	Dummy identifying individuals who report working from home in survey question [A].	individual
frequent WFH	Dummy identifying individuals who report working “always” or “frequently” from home in survey question [B].	individual
occasional WFH	Dummy identifying individuals who report working from home “sometimes” or “rarely” in survey question [B].	individual
WFH feasibility	A job is <i>WFH feasible</i> if the respondent does not rule out that WFH is possible in her job in survey question [C] or if she reports ever working from home in survey question [A]. WFH feasibility thus captures whether it is technologically feasible to perform a job at least partly from home.	individual
untapped WFH	Respondent never works from home (based on question [A]) but has a WFH feasible job. We assume employer-side (employee-side) restrictions to WFH if respondent would (would not) accept offer to WFH based on question [C].	individual
WFH capacity	Share of WFH feasible jobs in an occupation, a region, or an industry.	aggregate
untapped WFH capacity	Share of employees never working from home but with a WFH feasible job.	aggregate

Notes: The table outlines our terminology and the mapping of questions in the 2018 BIBB/BAuA Employment Survey into WFH concepts.

3. WFH capacities in Germany

3.1. Occupational WFH capacities

Fig. 1 depicts WFH capacities and (pre-pandemic) rates of actual WFH by occupation at the 2-digit level of the German Classification of Occupations (KldB 2010). The corresponding values are reported in Table A.1.¹² The total size of the bars corresponds to occupations’ WFH capacity, i.e., the percentage of WFH feasible jobs. The difference between total capacity and actual WFH is equal to (pre-pandemic) untapped WFH capacity, i.e., the fraction of employees who do not work from home despite having a WFH feasible job. Finally, untapped capacity is decomposed into the fraction of employees who do not work from home due to employer- and employee-side restrictions, respectively. The results show large differences across occupations. WFH capacities range from about 16 percent for “Drivers and Operators of Vehicles” to roughly 97 percent for computer scientists and ICT workers. The distribution of WFH capacities also suggests a substantial variation within occupations as all values range strictly between 0 and 100 percent and show no evident clustering at the extremes. This heterogeneity also holds for narrower occupation groups in our data. Indeed, the portion of the variation in individual-level WFH feasibility explained by occupations increases only marginally from 27 to 30 percent when comparing 2-digit occupations (36 groups) to 3-digit occupations (139 groups). This corroborates important insights of Adams-Prassl et al. (2022) and Gottlieb et al. (2021), namely, that much of the relevant variation in WFH feasibility is driven by differences across jobs belonging to the *same* occupation.

Although WFH feasibility should, *a priori*, be independent of worker or employer tastes and characteristics, actual WFH is clearly subject to selection based on varying attitudes and needs. For instance, teachers and instructors (KldB=84) show a WFH rate of 85 percent pre-pandemic, amounting to about 91 percent of total WFH capacity. It is common for teachers to prepare their courses at home and employers typically do not restrict this arrangement. Overall, about one in four workers report ever working from home, implying that before the pandemic only less than half of the economy’s WFH capacity (56 percent) was used.

3.2. Determinants of WFH feasibility

The evident heterogeneity in WFH feasibility across and within occupations begs the question about its determinants. The unique combination of individual-level information on WFH feasibility, worker characteristics, and task profiles allows us to shed light on the source of this heterogeneity.

A key novelty of our analysis is that we can identify job tasks and work conditions that are most and least conducive to WFH feasibility in a way that is independent of researcher judgment. To this end, we estimate individual WFH feasibility as a function of job features and worker characteristics. Employees report, for instance, how often they carry heavy loads, monitor machines, or use a computer on the job—the full list including population means is reported in Table A.4. Omitting this information is likely to

¹² We also report the results for ISCO-08 classification (1-digit and 2-digit level) in Tables A.2 and A.3.

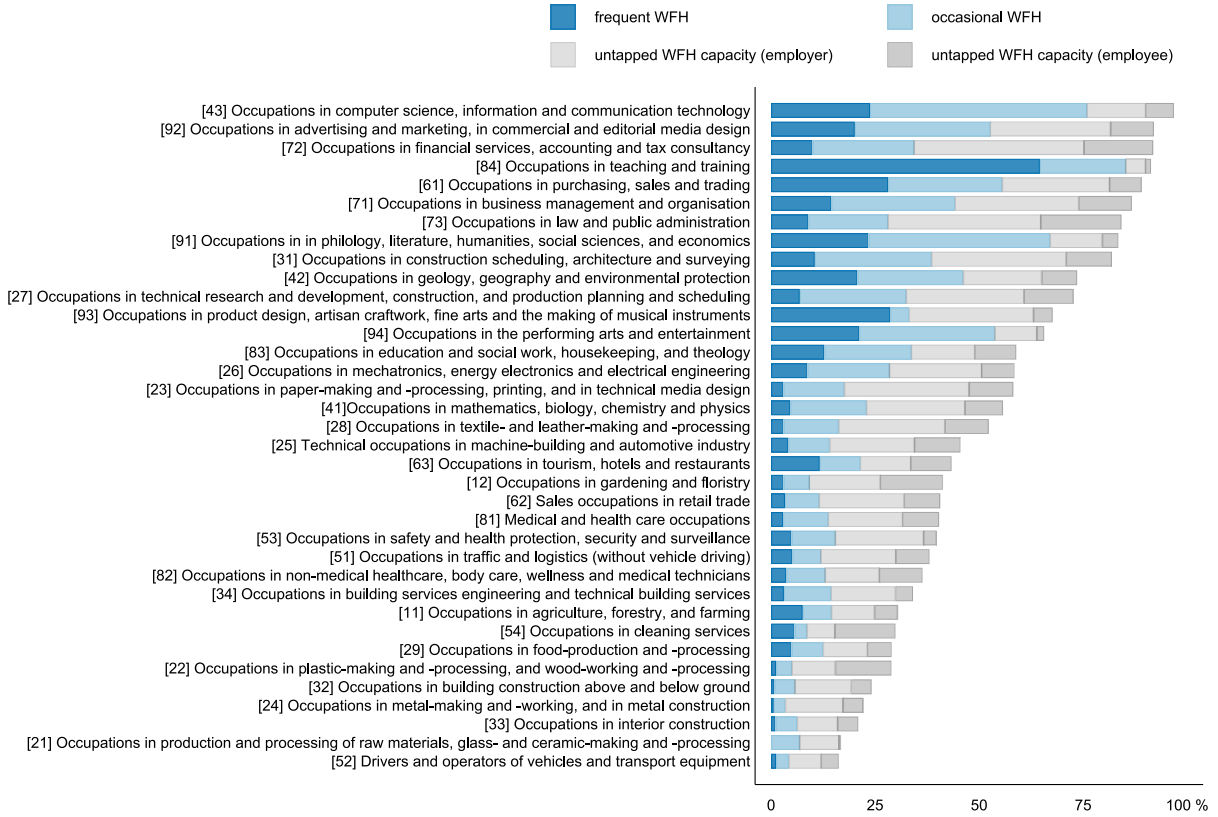


Fig. 1. Capacity to Work from Home by Occupation

Notes: The figure displays WFH capacities and pre-pandemic WFH usage by occupation (2-digit KldB). The underlying values are reported in Table A.1.

Source: 2018 BIBB/BAuA Employment Survey, own calculations.

severely overestimate the importance of demographic characteristics, such as gender or education, due to selection into different occupations or into different jobs within an occupation. We code each job task as one if respondent i indicates that she performs it frequently (and zero otherwise) and estimate the following linear probability model:

$$WFH_feasibility_i = \mathbf{T}_i' \delta + \mathbf{X}_i' \gamma + \alpha_{o(i)} + \alpha_{s(i)} + \varepsilon_i, \quad (1)$$

where $WFH_feasibility_i$ is our individual-level WFH feasibility indicator, $\mathbf{T}_i$ is the vector containing tasks and work conditions, $\alpha_{o(i)}$ denotes occupation fixed effects at the 2-digit level, and $\alpha_{s(i)}$ is a set of industry fixed effects (identifying 21 distinct industries). $\mathbf{X}_i$ is a vector of worker characteristics including gender, age, monthly wage, contractual working hours, tenure at the firm, and a set of dummies identifying respondents who are married, have children under the age of 11 living in the household, hold an academic degree, work in a firm with more than 100 employees, or have a migration background, respectively.

The OLS results are presented in Fig. 2. The left plot shows the estimates associated with job tasks, the right plot presents the estimates for background characteristics. We report the estimates from the full specification (in black) and from two baseline specifications (in blue), which estimate WFH feasibility as a function of only job tasks (left plot) or only individual characteristics (right plot). Cognitive and manual tasks are labeled (c) and (m), respectively. The full set of results including point estimates and their standard errors are reported in Table A.5. In the baseline specification, job tasks alone explain about 30 percent of the individual variation in WFH feasibility. The estimates imply that the likelihood of WFH feasibility increases strongly when the job requires frequent computer usage (14 p.p.), “advertising, marketing, PR” (6 p.p.) and “developing, researching, constructing” (7 p.p.). By contrast, the job features “work standing up” and “nursing, caring, healing” are the least conducive to WFH, reducing the likelihood of WFH feasibility by 13 p.p. and 7 p.p., respectively. There is an evident pattern indicating that WFH feasibility is positively associated with cognitive tasks and negatively correlated with manual tasks, consistent with previous findings (Mergener, 2020). Controlling for occupation, industry, and background characteristics in the full specification increases the R-squared to .37 and attenuates the estimated coefficients for job tasks. For instance, the marginal impact of working with a computer on the likelihood of a job being WFH feasible decreases from 14 p.p. to 9 p.p. Yet, most estimates do not lose their statistical significance. The task content of jobs thus appears to constitute the main determinant of WFH feasibility also within occupations and industries.

The estimation results for worker characteristics show the importance of accounting for job tasks and work conditions (right plot of Fig. 2). For instance, while women are on average 12 p.p. more likely to work in a WFH feasible job (holding other background

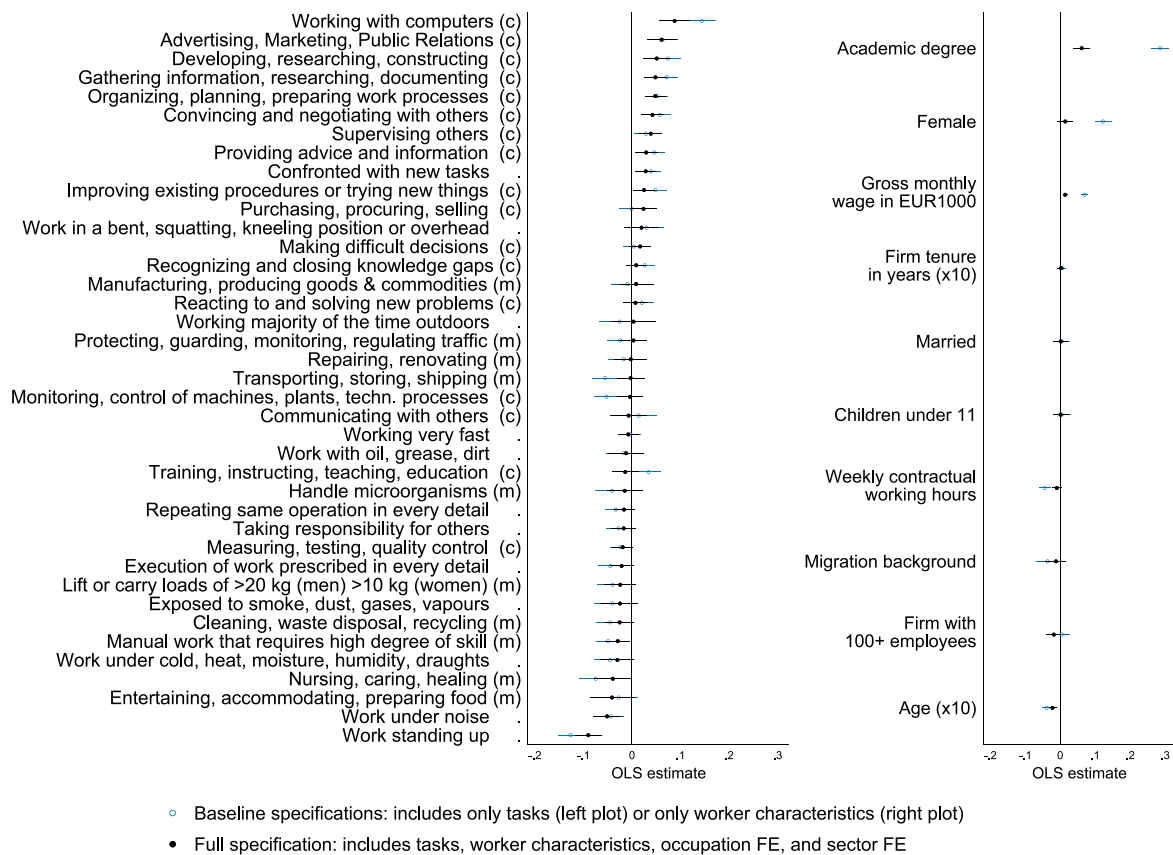


Fig. 2. Determinants of WFH Feasibility

Notes: The figure reports the estimates from regressing WFH feasibility on job tasks/ working conditions, worker characteristics, occupation fixed effects, and industry fixed effects (Eq. (1)). The baseline specifications include only job tasks (left plot) or only worker characteristics (right plot). The full specification includes job tasks, worker characteristics, occupation fixed effects, and industry fixed effects. Estimates are sorted by size in the full specification. Regressions use survey weights. Standard errors are robust to heteroskedasticity. Confidence intervals are reported at the 95% level. The full estimation results are reported in Table A.5.

characteristics constant), the effect reduces to 1 p.p. and becomes statistically insignificant when accounting for occupation, industry, and job tasks. The estimate for academic degree drops from 29 p.p. to only 6 p.p. in the full specification. Similarly, the estimates for age, migration background, wage, and working hours are much closer to zero in the full specification. In fact, the reductions in estimate sizes are almost entirely driven by conditioning on task profiles. Occupation and industry fixed effects instead only add little explanatory power and cause only marginal changes to the estimates (see full results in Table A.5).

However, some coefficients on worker characteristics remain statistically different from zero. For instance, holding an academic degree increases the chance of WFH by 6 p.p. and ten-year older employees have on average a 2 p.p. lower likelihood of reporting a WFH feasible job, all else equal. Although small, statistically relevant estimates can reflect two sources of bias. One is that our account of task profiles does not capture the full variation in task content. For example, “working with a computer” may encompass significantly different activities for high-skilled and lower-skilled employees. While conducting scholarly research or writing an academic article on a PC may be easily performed at home, serving clients at the counter of a bank is not. Thus, a significant estimate for holding an academic degree may reflect this type of omission. A second reason is measurement error in the sense that respondents may judge the WFH feasibility of the same job differently. For instance, younger employees could be more aware of technological solutions allowing to perform certain tasks at home. The results suggest that these types of biases are limited.

To further assess whether differences in task composition are the main driver of differences in WFH feasibility, we also conduct a variance decomposition exercise following Gottlieb et al. (2021). The results are reported in Table A.6. We find that tasks and work conditions alone explain 11.6 percent of the variance in WFH feasibility, plus a further 9.6 percent when adding the covariance with occupation fixed effects. By contrast, worker characteristics, occupation fixed effects, and industry fixed effects account for only .9 percent, 7.1 percent, and .7 percent of the variance, respectively.



Fig. 3. Determinants of Untapped WFH

Notes: The figure reports OLS estimates of two separate regressions of untapped WFH on job tasks/ working conditions, individual characteristics, occupation fixed effects, and industry fixed effects (Eq. (1)). Results in blue (black) use employee-side (employer-side) untapped WFH as the dependent variable. The reference group corresponds to employees working from home at least occasionally. Regressions use survey weights. Standard errors are robust to heteroskedasticity. Confidence intervals are reported at the 95% level. The full estimation results are reported in Table A.7.

3.3. Determinants of untapped WFH

By the start of the Covid-19 pandemic in early 2020, most of the WFH capacity in Germany had remained unexploited. According to the BIBB/BAuA Survey, about two-thirds of the untapped capacity is due to employer-side restrictions, i.e., to employees with WFH feasible jobs, who would like to work from home but do not, and one-third is the consequence of a lack of desire to WFH by employees. Pre-pandemic employer and employee survey evidence, e.g., reported in Grunau et al. (2019), illustrates that the major reasons for employee-side restrictions relate to a high appreciation of presence at the workplace in the corporate culture. Employers additionally mention data protection and data security concerns to be important. The lack of technical means does not range among the primary reasons, neither from the employee nor from the employer's perspective. Temporal and spatial distance is seen by both employers and employees as complicating collaboration with colleagues. Another important reason for employee-side restrictions is individuals' desire "to keep private and professional life separate".

To shed light on how untapped WFH correlates with task profiles and worker characteristics, we re-estimate Eq. (1) separately, using dummies identifying untapped WFH due to employer-side restrictions and due to employee-side restrictions as dependent variables. Individuals reporting working from home at least occasionally constitute our comparison group in both specifications (i.e., workers without WFH feasible jobs are excluded from the analysis). Fig. 3 reports the results of the full specification (including task profiles, worker characteristics, occupation fixed effects, and industry fixed effects as independent variables). The blue coefficients show point estimates and 95 percent confidence intervals for employee-side untapped WFH, the black coefficients show the results for employer-side untapped WFH. The full results are reported in Table A.7.

The OLS estimates indicate that working at a larger firm significantly increases the likelihood of reporting employee-side untapped WFH (4 p.p.), but has no statistically significant effect on reporting untapped WFH due to employer-side restrictions (right plot). This result is in line with previous findings, showing that larger firms are more likely to offer WFH arrangements to their employees (see e.g., Grunau et al., 2019). Employee gender, migration background, marital status, or children living in the household are not significantly correlated with the likelihood of untapped WFH. Younger workers are more likely to report employer-side restrictions preventing WFH but are not more likely to work from business premises because they have no desire to WFH. By contrast, workers with higher weekly working hours are significantly more likely to forgo working from home for both

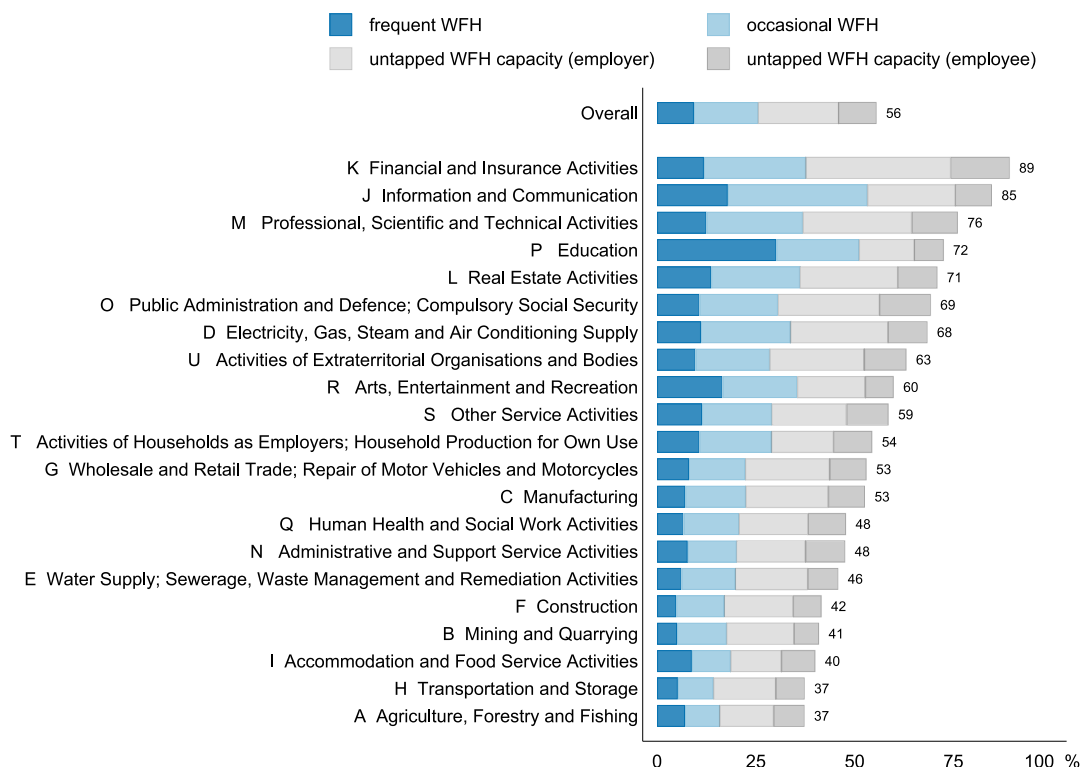


Fig. 4. Capacity to Work from Home by Sector

Notes: The figure displays WFH capacities and pre-pandemic WFH take-up by sector (NACE main sections) and in the overall economy. All values are reported in Table A.8.

Source: 2018 BIBB/BAuA Employment Survey, Employment Statistics of the Federal Employment Agency (BA) 2019, own calculations.

employer-side and employee-side reasons. The same is true for workers without an academic degree and workers with lower wages, all else equal.

The fact that higher-skilled workers are more likely to work from home when having a WFH feasible job is also reflected in the OLS estimates for job tasks and work conditions (left plot). Employees who are required to supervise others, conduct research, or negotiate with others are significantly less likely to report WFH restrictions. For example, employees required to provide advice and information are 5 p.p. less likely to forgo WFH due to employee-side restrictions and 6 p.p. less likely to forgo WFH due to employer-side restrictions. By contrast, individuals whose work is prescribed in detail or who conduct highly repetitive work report both employer-side and employee-side restrictions significantly more often.

3.4. Distribution of WFH capacities in the economy

We measure the aggregate WFH capacity in the German economy as well as the geographical and industry-level distribution of WFH feasible jobs by first collapsing our employee-level WFH feasibility indicator (population-weighted) to the occupation level (2-digit German Classification of Occupations, KldB 2010, excluding military services). Next, we combine the resulting shares with 2019 data from the Federal Employment Agency (BA) on occupational employment counts in the overall economy, in each German county (401 *Kreise* and *kreisfreie Städte*), and in each industry (88 2-digit NACE industries) and aggregate over occupations. We use the same approach to compute (pre-pandemic) rates of actual WFH as well as untapped WFH capacities in industries and counties.

It should be noted that regional employment statistics distinguish between employment at the *county of work* and at the *county of residence*. Using the former to construct our measure yields a distribution of WFH feasible jobs independent of employees' place of residence while using the latter allows measuring local shares of employees who can work from home independent of the location of their job. In the following, we restrict our scope to the former case as both approaches yield very similar results.¹³

¹³ Discrepancies are essentially due to cross-county commuting. The correlation between county-level WFH capacities calculated from both approaches is .81. For completeness, we publish our WFH capacity index based on both approaches in our online repository.

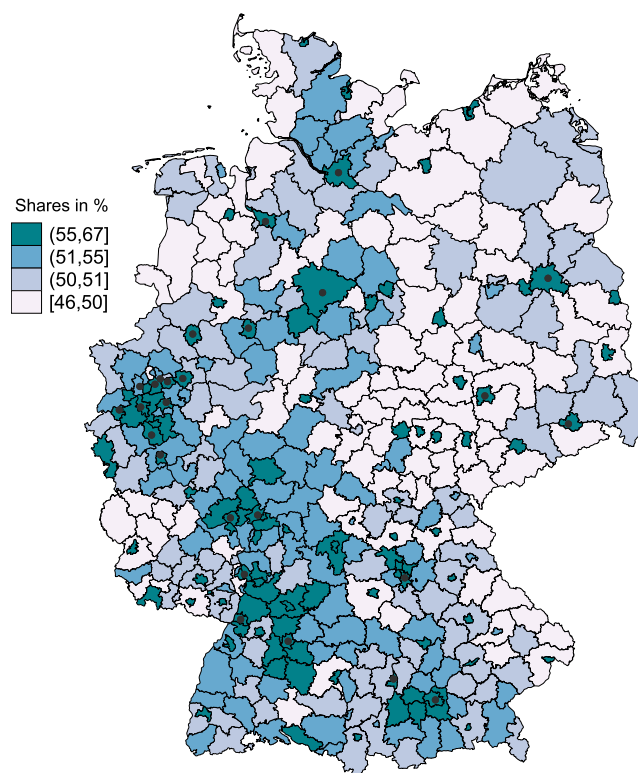


Fig. 5. Distribution of WFH Capacity in Germany

Notes: The map depicts the percentage of WFH feasible jobs across German counties by quartile of overall WFH capacity. Black dots represent cities with more than 250,000 inhabitants.

Source: 2018 BIBB/BAuA Employment Survey, Employment Statistics of the Federal Employment Agency (BA) 2019, own calculations.

Overall, 56 percent of jobs in Germany can be performed entirely or partly from home.¹⁴ Fig. 4 reports WFH capacities and pre-pandemic rates of actual WFH for the overall economy and by sector (NACE main sections). The results for all 2-digit industries are reported in Table A.9. There is a large variation in WFH capacity across industries, with values ranging from 37 percent in the transportation or agricultural sector to nearly 90 percent in highly digitized sectors, such as the ICT sector and the financial sector. In most sectors, actual WFH rates before the pandemic fall far below their capacity. Only employees in education and the ICT sector used well over half of their WFH capacity. In all industries, pre-pandemic untapped capacities are mainly driven by employer-side rather than employee-side restrictions.

Fig. 5 depicts the geographic distribution of WFH feasible jobs across the 401 German counties. Note that by construction, industry-level and regional variation in WFH capacity is determined by the occupational composition in each industry and county, respectively. The reliability of these results thus rests on the assumption that occupational WFH capacities in different industries or counties do not significantly differ from their national averages reported in Fig. 1. The map reveals a clear divide between East and West Germany and between densely populated, urban counties and rural counties with lower population density. While on average 59 percent of jobs in West Germany (including Berlin) can be done from home, only 50 percent of jobs are WFH feasible in East Germany. Urban–rural inequalities are even more pronounced: WFH capacity amounts to roughly 65 percent in counties with 500,000 inhabitants or more, compared to 53 percent in the rest of the country. Fig. A.1 in the Appendix shows a strong correlation of .88 between WFH capacity and population density across counties, reflecting the specialization of urban centers in digitized, knowledge-intensive industries.

4. WFH capacity and the covid-19 pandemic

4.1. Predicting WFH outcomes during the covid-19 pandemic

To assess whether our measure is a suitable predictor of actual WFH outcomes during the Covid-19 pandemic, we leverage WFH data at the industry, occupation, regional, and individual level. For an industry-level investigation, we use the ifo Business Survey

¹⁴ In the aggregate, the discrepancy between WFH capacity calculated from the survey alone and calculated employing occupational employment counts is only about 1 percentage point (p.p.).

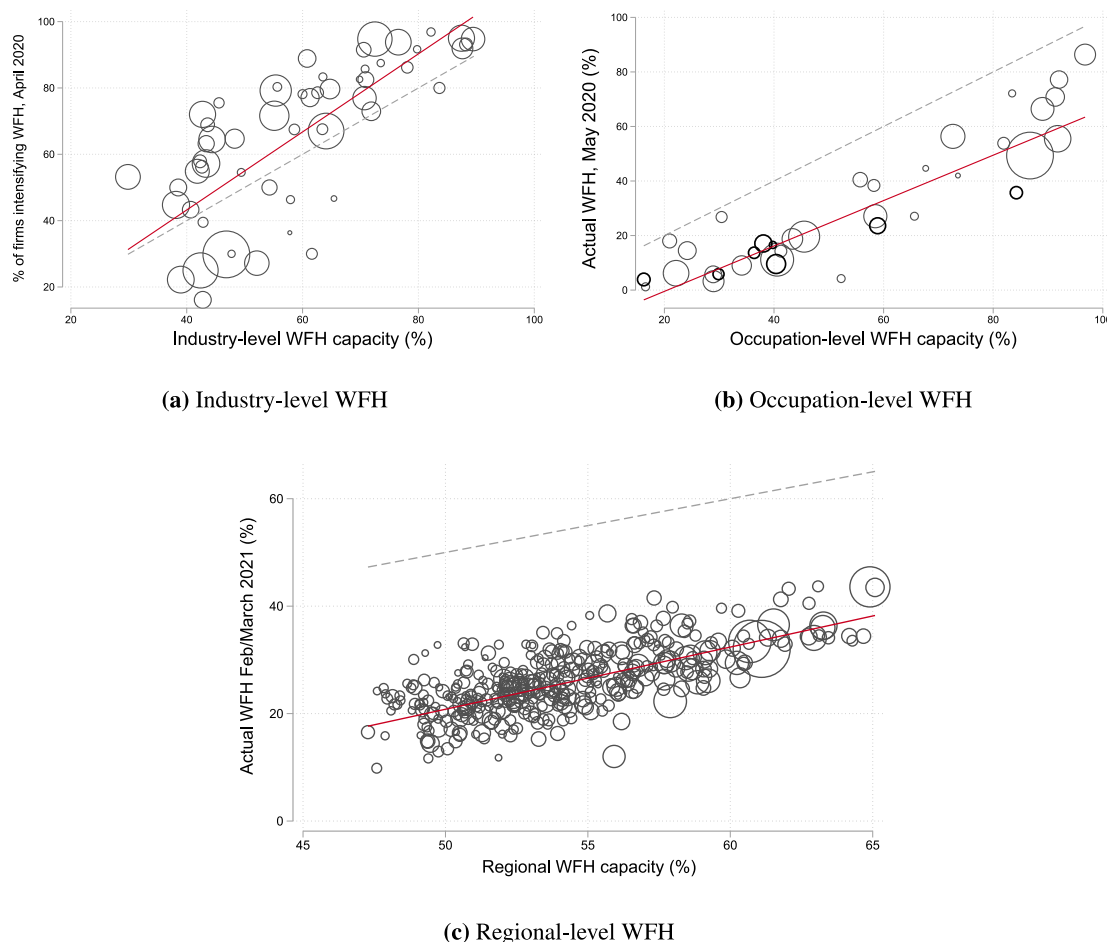


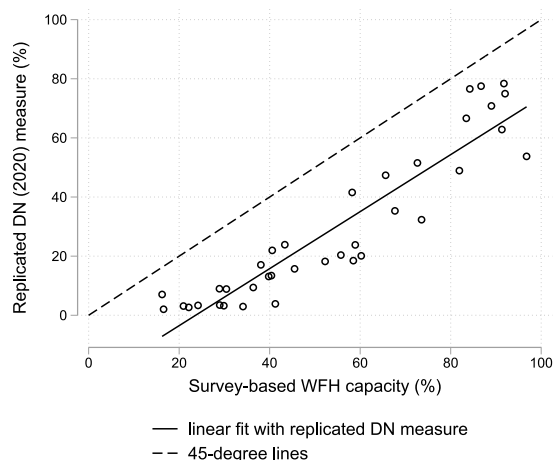
Fig. 6. Predicting Actual WFH during the Covid-19 Pandemic

Notes: Figure (a) reports the linear fit between industry-specific shares of firms reporting intensified WFH in the April 2020 wave of the ifo Business Survey (IBS) and industry-level WFH capacity. 56 industry-level observations (2-digit NACE level) are computed from 7,227 firm-level responses (only industries with 10 or more respondents). Figure (b) reports the linear fit between the occupation-specific share of employees reporting WFH in the May 2020 wave of the IAB High-Frequency Online Personal Panel (HOPP) and occupational WFH capacity. 36 occupation-level observations (2-digit KldB 2010 level) are computed from 7,460 individual-level responses (only occupations with 10 or more respondents). Bold black markers are 2-digit occupations with more than 50 percent employment in essential 3-digit occupations. Figure (c) reports the linear fit between the regional share of employees reporting working from home mostly or entirely in the February/March 2021 wave of the infas/infas360 survey and county-level WFH capacity at the place of residence. The 45-degree lines are highlighted in dashed gray. All observations are weighted with total employment in June 2019 according to the Federal Employment Agency (BA).

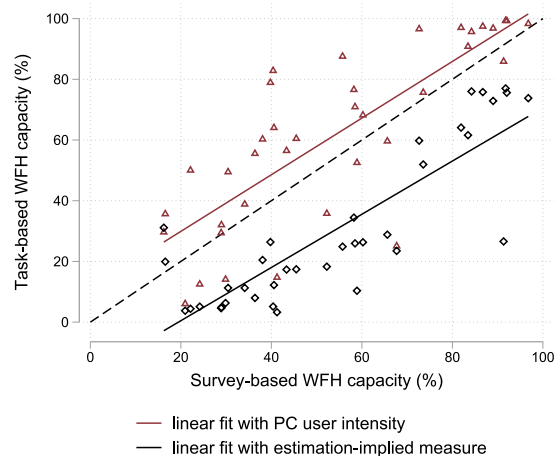
(IBS), a monthly, nationally-representative survey of roughly 9,000 German companies from all relevant industries (see [Buchheim et al., 2020](#) and [Sauer and Wohlrabe, 2020](#) for details). We use data from the April 2020 wave, in which companies were questioned about managerial responses to the Covid-19 crisis.¹⁵ Nearly two-thirds of the firms indicated “relying more heavily on working from home” as part of their strategy to cope with the crisis. The measure thus captures efforts to expand WFH both at the intensive and the extensive margin. We compute industry-level shares of firms relying on WFH and plot these against our measure of WFH capacity at the 2-digit industry level in [Fig. 6\(a\)](#). The size of the bubbles is proportional to total employment in June 2019. The 45-degree line is highlighted in dashed gray. The plot shows that our measure of WFH capacity performs remarkably well in predicting WFH patterns across industries. The index explains about 58 percent of the variation in actual WFH during the pandemic. The correlation between industry-specific WFH capacity and WFH take-up is .76 and highly statistically significant.¹⁶

¹⁵ The first nationwide containment measures were implemented in Germany between late March and early May 2020 with the closure of restaurants and bars, as well as daycare facilities, schools, universities, and non-essential shops, followed by a gradual loosening of these measures.

¹⁶ Excluding industries with over 50 percent employment in essential occupations (based on the classification at 3-digit KldB level in [Koebe et al., 2020](#)) yields a slightly stronger correlation (.78) and our WFH index explains about 61 percent of the variation in pandemic WFH.



(a) Comparison with replicated DN measure



(b) Comparison with PC intensity and estimation-implied measure

Fig. 7. Comparison of Survey-Based with Task-Based Measures of WFH Capacity

Notes: The figures report linear fits between the task-based measure of WFH capacity and our survey-based measure at the 2-digit occupation level. The replicated DN measure in (a) uses tasks and work conditions of the BIBB/BAuA that are most similar to the original conditions used in DN (2020). The estimation-implied measure in (b) is computed based on the task-exclusion approach using tasks and work conditions that constitute negative and statistically significant predictors for WFH feasibility (see Section 3.2). PC use intensity in (b) is the share of employees who report frequently working with a computer. Source: 2018 BIBB/BAuA Employment Survey, own calculations.

With respect to the occupation level, we compare our WFH measure to actual WFH rates surveyed in the IAB High-Frequency Online Personal Panel (HOPP), a monthly online panel survey developed by the Institute for Employment Research (IAB) (Sakshaug et al., 2020; Haas et al., 2021).¹⁷ We use the May 2020 wave, in which about 7,500 employees report whether they worked from home in the previous week (mean = .32). We compute occupation-specific rates in actual WFH and plot these against our measure of WFH capacity at the 2-digit occupational level (Fig. 6(b)). Observations are weighted with total employment in June 2019, assigning more importance to larger occupations. Essential occupations, such as “Medical and health care occupations”, are highlighted in bold black.¹⁸ The plot demonstrates that our measure of occupational WFH capacity is strongly associated with actual WFH during the pandemic. WFH feasibility constraints explain about 86 percent of the variation in actual WFH. The correlation between the two variables is .92 and highly statistically significant. Excluding essential occupations yields a marginally stronger correlation (.93) and our WFH index explains a slightly higher share of the variation in WFH during the pandemic (87 percent). Overall, essential occupations do not appear to constitute outliers, i.e., we find a strong correlation between WFH feasibility and actual WFH during the pandemic also for these occupations.

To investigate the predictive power of our measure at the individual level, we use the HOPP data for an empirical exercise similar to that of Gottlieb et al. (2021) to assess the predictive power of our measure at the individual level. Since we do not observe both individual WFH feasibility and actual WFH in the same dataset, we regress individual WFH feasibility in the BIBB/BAuA data on employee characteristics (gender, migration background, children below age 11, age, academic degree) and occupations (2-digit KldB 2010) and use the resulting coefficients to impute individual WFH feasibility in the HOPP data. Fig. A.2 in the Appendix plots predicted individual-level WFH feasibility, grouped into 20 equal-sized bins, against the share of workers in each bin that reported working from home in May 2020. The correlation between predicted WFH feasibility and individual WFH during the pandemic is positive and highly statistically significant.

Finally, we compare our regional measure of WFH capacity with county-level WFH data from the infas/inf360 survey, which documents the share of employees working “mostly or entirely” from home in February/March 2021.¹⁹ According to the survey, 27 percent of employees spent most of their working hours at home.²⁰ Fig. 6(c) demonstrates that our regional measure of WFH capacity is a strong predictor of regional differences in actual WFH during the crisis. WFH capacity alone explains 56 percent of the variation in actual WFH across counties.

¹⁷ The data and data documentation are provided internationally at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB): <https://fdz.iab.de/en.aspx>.

¹⁸ We closely follow Koebe et al. (2020) to classify occupations into essential and non-essential.

¹⁹ See Alipour, Falck, Follmer, Gilberg, Nolte, and Frank (2021b) for details on the survey.

²⁰ This is notably lower than the 56 percent WFH capacity we estimate, most likely reflecting the fact that our measure also captures WFH at intensities below 50 percent of working hours.

4.2. Applications

The fact that WFH feasibility is a good predictor of the observed variation in actual WFH during the crisis offers scope for broad applications of our measures. As the regional spread of Covid-19 crucially depends on the frequency of face-to-face contacts, county-level WFH capacity represents a useful proxy for the potential to socially distance employees from each other. For instance, using this measure, [Alipour, Fadinger, and Schymik \(2021a\)](#) show that working from home significantly reduced SARS-CoV-2 infections and related deaths during the first wave in Germany. The analyses suggest that the effect of WFH appeared strongest in the weeks preceding the national lockdown measures, as workers and firms started to socially distance by transitioning to WFH. Once containment measures were imposed in late March 2020, millions of employees who could not work from home were registered for short-time work, thus reducing their working hours and physical presence at work. Hence, business closures and WFH appear to be substitute policies to some extent. Comparing actual WFH rates to WFH capacities can thus inform policymakers about unused WFH potential and support discussions about mandates or incentives to shift the economy toward its full WFH capacity. Using WFH capacity as a predictor of actual firm-level WFH, [Alipour, Fadinger, and Schymik \(2021a\)](#) also demonstrate that businesses that could go remote more easily responded significantly better to the Covid-19 shock, reporting better business outcomes and filing fewer applications for short-time work.

Besides total WFH capacity, the level of untapped capacity also has valuable applications. For instance, it proves to be a useful predictor of where in the economy the Covid-19 shock triggered the strongest organizational adjustments toward WFH. Using online job vacancy posting data for Germany, [Alipour, Langer, and O’Kane \(2021c\)](#) show that the share of job postings with an explicit option to WFH in the job description more than tripled between 2019 and 2021. The strongest growth occurred in occupations that previously exhibited the largest untapped capacity, suggesting that the Covid-19 shock prompted firms to increasingly exploit their untapped WFH potential by starting to advertise WFH feasible jobs with WFH options.

Our regional measure of WFH capacity is a useful input not only to models concerned with the geographic spread of SARS-CoV-2 (e.g., [Felbermayr et al., 2021](#)), but also to models addressing the changing spatial distribution of other variables, including the consumption of housing, goods, or services. Understanding the (post-)pandemic geography of consumption and its driving forces has attracted growing interest in the literature. For instance, the transition toward WFH not only shifts consumption of housing from dense urban centers with high WFH capacity to less densely populated suburban rings but also withdraws expenditure on consumer services from the centers of the metropolitan areas (e.g., [Althoff et al., 2022](#); [Barrero et al., 2021](#); [Brueckner et al., 2021](#); [Davis et al., 2021](#); [Delventhal and Parkhomenko, 2020](#); [Ramani and Bloom, 2021](#)). As a consequence, the new organization of work is likely to generate critical economic consequences for many lower-skilled individuals who depend on distance workers’ expenditures. Thus, determining the magnitude, direction, and persistence of the shifts toward WFH remains of great importance for the post-Covid era. Accurate and detailed information on the distribution of WFH feasible jobs, differences in regional capacities, and potential for shifts toward WFH triggered by the Covid-19 shock is thus key to such endeavors.

5. Comparison of task-based and survey-based measures

How does our survey-based measure of WFH capacity compare to popular task-based measures à la [DN \(2020\)](#)? The rich data contained in the BIBB/BAuA Survey allows us to construct a task-based measure of WFH feasibility following the task-exclusion approach proposed by [DN](#). Using the BIBB/BAuA Survey instead of O*NET data enables us to compute and compare WFH feasibility for Germany at the individual level.²¹ The tasks and work conditions included in our data do not exactly match the tasks included in O*NET. We thus choose the relevant job characteristics that are most similar to those determined by [DN](#). In particular, we assume that an employee’s job is incompatible with *full-time* WFH if at least one of 11 conditions is met. These include, for instance, frequently carrying heavy loads, frequently handling microorganisms, working the majority of the time outdoors, or never using the Internet or email.²² The full list of conditions is reported in [Table A.10](#). Overall, the task-exclusion approach suggests that 34 percent of jobs can be performed entirely at home, a value that is remarkably close to the 37 percent calculated by [DN](#) for the German economy based on O*NET data. At the individual level, 29 percent of jobs are classified as WFH feasible according to both the replicated [DN](#) measure and our survey-based indicator (see [Table 2](#)). 28 percent of jobs are classified as WFH feasible according to the survey-based indicator but not according to the task-exclusion approach. Following the logic of [DN](#), the task-exclusion approach aims at reflecting opportunities for working full-time from home. Thus, this portion can be interpreted as jobs that are only part-time WFH feasible. Only 5 percent of survey respondents rule out the possibility of WFH, while the task-exclusion measure suggests that WFH is feasible full-time. While this inconsistency may reflect the fact that the task-exclusion measure is too lax at identifying job characteristics that preclude WFH, we cannot reject the possibility of measurement error in the survey.

Plotted at the occupational level, both measures show a remarkable similarity. [Fig. 7\(a\)](#) reports the linear fit between the replicated [DN](#) measure and our survey-based measure. We find a strong correlation of .93 between the two approaches ($R^2 = .86$).

²¹ See e.g., [Gottlieb et al. \(2021\)](#) and [Lewandowski et al. \(2022\)](#) who demonstrate that cross-country differences in task content within the same occupations are sizeable.

²² Specifically, if respondents rate any of the following as true, we code their job as not feasible for full-time WFH: Never using the Internet or E-Mail processing; Frequently lifting or carrying loads of more than 10 kg (women) or 20 kg (men); Frequent exposure to smoke, dust, gases, or vapor; Frequent exposure to cold, heat, moisture, humidity or draughts; Frequently handling microorganisms such as pathogens, bacteria, moulds or viruses; Frequently working with oil, grease or dirt; Works the majority of time outdoors; Frequently repairing or renovating; Frequently protecting, guarding, monitoring, or regulating traffic; Frequently cleaning, disposing of waste or recycling; Frequently monitoring or controlling machines, plants, or technical processes.

Table 2

Individual-level comparison of survey-based and task-based measure of WFH feasibility.
Source: BIBB/BAuA Employment Survey 2018, own calculations.

	Task-based WFH feasibility =1	Task-based WFH feasibility =0
Survey-based WFH feasibility = 1	28.9%	28.3%
Survey-based WFH feasibility = 0	5.2%	37.6%

Notes: The table compares our survey-based indicator with a task-based indicator of WFH feasibility at the individual level ($N = 17,160$). The task-based indicator is computed using the task-exclusion approach proposed by DN (2020) (see Table A.10 for details). Values of 1 indicate that WFH is feasible according to the corresponding measure.

The slope of the OLS line is statistically indistinguishable from one, and thus, effectively parallel to the 45-degree line. This suggests that the different measurement approaches primarily differ in terms of the estimated level of WFH capacity and much less with respect to the distribution across occupations. This discrepancy is consistent with part-time WFH feasible jobs that are captured in the survey but not in DN's index.

For further comparison, we compute two additional task-based measures inferred from our previous analysis of the determinants of WFH feasibility in Section 3.2. First, as working with a computer constitutes the strongest predictor of WFH feasibility, we compute the share of jobs that require frequent PC use as a simple proxy of WFH capacity. The second measure follows the task-exclusion approach by assigning zero WFH feasibility to jobs that require one or more of the tasks and work conditions that constitute negative and statistically significant predictors for WFH feasibility. These include frequently “nursing, caring, or healing”, frequently “working standing up”, frequently “working under noise”, and frequently “performing manual work that requires a high degree of skill, fast sequences of movements, or greater force”. We refer to this index as the estimation-implied measure.²³

Fig. 7(b) plots the two additional task-based measures against our survey-based measure at the occupational level. The results again show remarkable similarity with the survey-based approach. The slopes of the OLS lines of PC intensity and the estimation-implied measure are statistically indistinguishable from one (and thus parallel to the 45-degree line), suggesting that these measures differ, on average, only by a constant value. The correlation between PC intensity (the estimation-implied measure) and survey-based WFH is .80 (.85). The regression lines of the estimation-implied measure and the replicated DN index are even statistically indistinguishable, despite using entirely different job characteristics as exclusion criteria for WFH feasibility.

Overall, these results indicate that under reasonable assumptions, even very simple task-based measures of WFH capacity, such as the share of PC users, perform well at capturing differences across occupations. There is, however, greater sensitivity to the level of WFH capacity depending on the number and type of job characteristics deemed incompatible with WFH. This is consistent with the sizeable variation in task-based estimates for the German WFH capacity discussed above. Still, for most applications, task-based measures will constitute suitable inputs that accurately capture relevant variation in WFH capacity.

6. Concluding remarks

In a collective effort to reduce infection risk, the Covid-19 crisis has prompted a massive shift toward WFH. Evidence suggests that firms invested heavily to maintain business operations, while their employees were unable (or not allowed) to work from company premises (Barrero et al., 2021). We shed light on the feasibility constraints of WFH during the pandemic by developing a measure of WFH capacity for the German economy, drawing on a rich employment survey and administrative employment data. Unlike most previous studies, our measure reflects the self-assessment of employees of their own job, includes jobs that are only suitable for part-time WFH, and uses information specific to the German economy. We find that 56 percent of jobs can be done at least partially from home. WFH feasible jobs are largely located in urban, densely populated areas, and in highly digitized industries. Using individual-level data on tasks and work conditions, we demonstrate that heterogeneity in WFH feasibility is mostly explained by differences in task content. OLS estimates suggest that WFH feasible jobs are typically characterized by cognitive, non-manual tasks, and, in particular, by PC usage. By contrast, worker characteristics drive selection into actual WFH prior to the Covid-19 crisis. In particular, lower-wage and lower-educated workers were significantly less likely to WFH despite having a WFH feasible job.

We compare our survey-based measure with task-based measures of WFH capacity, which are very popular in the literature and typically rely on manually classifying the compatibility of tasks with WFH. The results reveal that task-based approaches capture differences in WFH capacity across occupations quite accurately on average, but vary in terms of the level of WFH capacity. We suggest that in settings with limited data availability, a simple measure of PC use intensity will constitute a suitable measure of WFH capacity.

We show that our WFH index constitutes a strong predictor of actual WFH outcomes during the crisis, at the occupation, industry, and county level, and discuss different applications in the context of Covid-19. As such, it is a useful measure to design targeted policies or evaluate social distancing mandates in the work context. It can provide a key element for models used in the burgeoning literature addressing the consequences of the Covid-19 shock for the organization of work and the spatial distribution of consumption.

²³ Notice that none of the features used to compute this measure correspond to the job characteristics used to replicate the DN index.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

See [Figs. A.1 and A.2](#) and [Tables A.1–A.10](#).

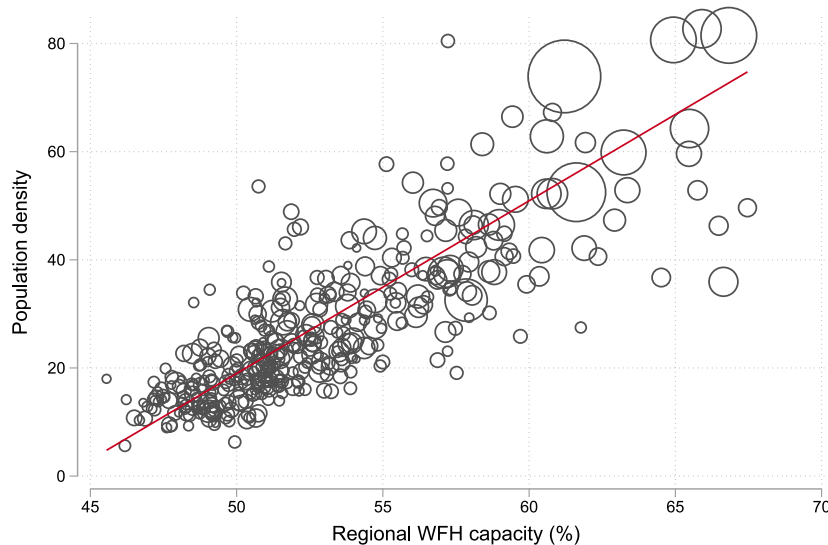


Fig. A.1. Correlation between Population Density and WFH Capacity

Notes: The figure shows the linear fit between county-level population density (total population relative to settled area in hectares) and county-level WFH capacity. The size of the bubbles is proportional to total employment.

Source: Destatis, Employment Statistics of the Federal Employment Agency (BA) 2019, own calculations.

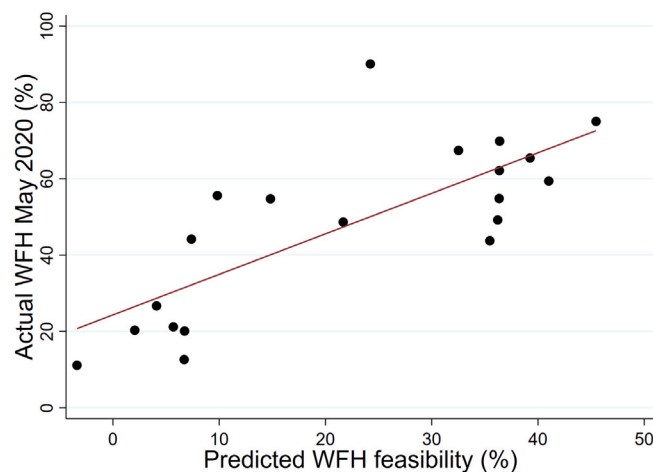


Fig. A.2. Predicting Actual Individual-Level WFH during the Covid-19 Pandemic

Notes: The figure shows the linear fit between individual-level actual WFH reported in May 2020 and predicted WFH feasibility. Individual WFH feasibility has been predicted in the BIBB/BAuA data based on employee characteristics (gender, migration background, child below age 11, age, academic degree) and occupations (2-digit KldB 2010) and subsequently imputed in the HOPP data. The binned scatterplot groups predicted WFH feasibility into 20 equal-sized bins and plots them against the share of workers in each bin that reported to actually WFH in May 2020.

Source: IAB High-Frequency Online Personal Panel (HOPP) May 2020, 2018 BIBB/BAuA Employment Survey, own calculations.

Table A.1

Capacity to work from home by occupation (KldB-10 2-digit).

Source: 2018 BIBB/BAuA Employment Survey, own calculations.

KldB-10 2-digit occupations	Frequent WFH	Occasional WFH	Untapped WFH (employer)	Untapped WFH (employee)	WFH capacity
11 Occupations in agriculture, forestry, and farming	7.591	6.928	10.32	5.601	30.44
12 Occupations in gardening and floristry	3.026	6.105	17.13	14.91	41.25
21 Occupations in production and processing of raw materials, glass- and ceramic-making and -processing	0	6.851	9.709	0	16.56
22 Occupations in plastic-making and -processing, and wood-working and -processing	1.210	3.779	10.44	13.48	28.91
23 Occupations in paper-making and -processing, printing, and in technical media design	2.978	14.62	29.97	10.67	58.23
24 Occupations in metal-making and -working, and in metal construction	0.618	2.806	13.84	4.863	22.13
25 Technical occupations in machine-building and automotive industry	4.126	9.940	20.36	11.04	45.50
26 Occupations in mechatronics, energy electronics and electrical engineering	8.770	19.66	22.12	7.939	58.49
27 Occupations in technical research and development, construction, and production planning and scheduling	6.899	25.59	28.29	11.86	72.65
28 Occupations in textile- and leather-making and -processing	3.026	13.23	25.50	10.38	52.26
29 Occupations in food-production and -processing	4.929	7.605	10.63	5.806	28.97
31 Occupations in construction scheduling, architecture and surveying	10.49	28.07	32.34	11.01	81.92
32 Occupations in building construction above and below ground	0.800	4.930	13.59	4.854	24.17
33 Occupations in interior construction	1.081	5.154	9.733	4.988	20.96
34 Occupations in building services engineering and technical building services	3.090	11.32	15.47	4.121	34.12
41 Occupations in mathematics, biology, chemistry and physics	4.621	18.31	23.64	9.161	55.74
42 Occupations in geology, geography and environmental protection	20.75	25.43	18.85	8.524	73.57
43 Occupations in computer science, information and communication technology	23.78	52.17	14.05	6.666	96.77
51 Occupations in traffic and logistics (without vehicle driving)	5.122	6.843	18.00	8.056	38.06
52 Drivers and operators of vehicles and transport equipment	1.200	3.058	7.772	4.187	16.24
53 Occupations in safety and health protection, security and surveillance	4.936	10.47	21.26	3.131	39.79
54 Occupations in cleaning services	5.681	2.936	6.740	14.52	29.88
61 Occupations in purchasing, sales and trading	28.14	27.41	25.81	7.645	89.00
62 Sales occupations in retail trade	3.346	8.229	20.43	8.569	40.58
63 Occupations in tourism, hotels and restaurants	11.68	9.773	12.10	9.804	43.36
71 Occupations in business management and organization	14.48	29.70	29.73	12.77	86.72
72 Occupations in financial services, accounting and tax consultancy	9.992	24.36	40.87	16.42	91.76
73 Occupations in law and public administration	8.975	19.12	36.71	19.06	84.23
81 Medical and health care occupations	2.915	10.82	17.86	8.832	40.39
82 Occupations in non-medical healthcare, body care, wellness and medical technicians	3.635	9.327	13.07	10.28	36.38
83 Occupations in education and social work, housekeeping, and theology	12.79	20.92	15.22	9.975	58.92
84 Occupations in teaching and training	64.61	20.63	4.756	1.526	91.32
91 Occupations in philology, literature, humanities, social sciences, and economics	23.47	43.60	12.52	3.857	83.45
92 Occupations in advertising and marketing, in commercial and editorial media design	20.12	32.60	28.86	10.43	92.02
93 Occupations in product design, artisan craftwork, fine arts and the making of musical instruments	28.64	4.545	29.86	4.637	67.68
94 Occupations in the performing arts and entertainment	21.21	32.60	10.03	1.791	65.63

Notes: The table displays WFH capacities and pre-pandemic WFH take-up by occupation (2-digit KldB 2010).

Table A.2

Capacity to work from home by occupation (ISCO-08 1-digit).

Source: 2018 BIBB/BAuA Employment Survey, own calculations.

ISCO-08 1-digit occupations	Frequent WFH	Occasional WFH	Untapped WFH (employer)	Untapped WFH (employee)	WFH capacity
0 Armed forces occupations	1.542	6.064	29.89	23.16	60.66
1 Managers	29.02	39.94	13.08	6.368	88.43
2 Professionals	32.89	35.74	16.01	5.906	90.55
3 Technicians and associate professionals	9.374	19.36	26.25	11.50	66.49
4 Clerical support workers	6.440	12.95	34.60	15.59	69.72
5 Services and sales workers	4.276	8.101	15.06	9.104	36.56
6 Skilled agricultural, forestry and fishery workers	2.185	6.090	11.95	11.79	32.02
7 Craft and related trades workers	1.845	5.104	15.83	5.876	28.67
8 Plant and machine operators and assemblers	1.085	1.638	11.19	7.279	21.20
9 Elementary occupations	1.592	2.523	12.17	8.656	24.94

Notes: The table reports WFH capacities and pre-pandemic WFH take-up by occupation (1-digit ISCO 2008).

Table A.3

Capacity to work from home by occupation (ISCO-08 2-digit).

Source: 2018 BIBB/BAuA Employment Survey, own calculations.

ISCO-08 2-digit occupations	Frequent WFH	Occasional WFH	Untapped WFH (employer)	Untapped WFH (employee)	WFH capacity
11 Chief executives, senior officials and legislators	39.77	40.26	6.758	9.398	96.19
12 Administrative and commercial managers	30.72	42.55	16.67	3.165	93.17
13 Production and specialized services managers	25.82	41.02	13.16	8.352	88.35
14 Hospitality, retail and other services managers	29.23	26.59	8.634	2.730	67.19
21 Science and engineering professionals	12.83	41.60	26.85	12.26	93.63
22 Health professionals	7.341	15.87	22.84	6.720	52.75
23 Teaching professionals	66.00	20.41	4.685	0.781	91.68
24 Business and administration professionals	25.33	47.30	18.81	5.658	97.18
25 Information and communications technology professionals	23.50	52.75	14.46	6.930	97.73
26 Legal, social and cultural professionals	23.54	39.83	20.00	7.105	90.47
31 Science and engineering associate professionals	7.632	18.95	27.04	9.418	63.03
32 Health associate professionals	1.994	10.92	17.36	8.197	38.44
33 Business and administration associate professionals	13.29	21.85	35.99	16.04	87.25
34 Legal, social, cultural and related associate professionals	11.54	20.72	16.21	9.468	57.94
35 Information and communications technicians	19.09	48.27	15.56	4.635	87.69
41 General and keyboard clerks	9.768	15.34	37.09	17.93	80.50
42 Customer services clerks	4.958	11.44	41.09	19.01	76.56
43 Numerical and material recording clerks	5.926	11.96	31.02	13.05	62.04
44 Other clerical support workers	2.266	12.02	30.08	12.62	56.97
51 Personal services workers	5.136	8.476	13.24	8.693	35.55
52 Sales workers	3.992	8.393	19.43	8.848	40.66
53 Personal care workers	4.618	8.284	8.925	13.20	35.10
54 Protective services workers	2.204	5.471	16.18	2.472	26.33
61 Market-oriented skilled agricultural workers	2.285	4.727	12.50	12.34	31.85
62 Market-oriented skilled forestry, fishery and hunting workers	0	35.68	0	0	35.68
71 Building and related trades workers (excluding electricians)	1.375	3.751	10.37	3.617	19.14
72 Metal, machinery and related trades workers	1.256	3.370	14.83	6.609	26.07
73 Handicraft and printing workers	5.351	3.021	22.39	12.90	43.66
74 Electrical and electronics trades workers	4.527	11.39	24.57	3.573	44.07
75 Food processing, woodworking, garment and other craft and related trades workers	0.222	5.365	15.34	8.039	28.99
81 Stationary plant and machine operators	1.074	1.735	15.78	8.791	27.39
82 Assemblers	0.362	1.353	10.67	16.63	29.01
83 Drivers and mobile plant operators	1.219	1.620	8.087	4.579	15.52
91 Cleaners and helpers	1.891	3.981	8.171	13.97	28.01
92 Agricultural, forestry and fishery labourers	0	0	32.56	0	32.56
93 Labourers in mining, construction, manufacturing and transport	0.483	1.260	16.77	7.066	25.57
94 Food preparation assistants	1.198	0	6.329	4.834	12.36
96 Refuse workers and other elementary workers	5.749	6.449	6.911	6.244	25.35

Notes: The table reports WFH capacities and pre-pandemic WFH take-up by occupation (2-digit ISCO 2008).

Table A.4

Tasks and work conditions in the 2018 BIBB/BAuA survey.

Source: 2018 BIBB/BAuA Employment Survey, weighted, own calculations.

Survey label	Task or work condition	Mean
F303	Manufacturing, producing goods & commodities	0.17
F304	Measuring, testing, quality control	0.47
F305	Monitoring, control of machines, plants, techn. processes	0.26
F306	Repairing, renovating	0.17
F307	Purchasing, procuring, selling	0.19
F308	Transporting, storing, shipping	0.26
F309	Advertising, Marketing, Public Relations	0.09
F310	Organizing, planning, preparing work processes	0.46
F311	Developing, researching, constructing	0.13
F312	Training, instructing, teaching, education	0.22
F313	Gathering information, researching, documenting	0.57
F314	Providing advice and information	0.58
F315	Entertaining, accommodating, preparing food	0.10
F316	Nursing, caring, healing	0.16
F317	Protecting, guarding, monitoring, regulating traffic	0.22
F318	Working with computers	0.70
F320	Cleaning, waste disposal, recycling	0.28
F600_01	Work standing up	0.54
F600_03	Lift or carry loads of > 20 kg (men) > 10 kg (women)	0.23
F600_04	Exposed to smoke, dust, gases, vapors	0.13
F600_05	Work under cold, heat, moisture, humidity, draughts	0.20
F600_06	Work with oil, grease, dirt	0.18
F600_07a	Manual work that requires high degree of skill, fast sequences of movements, or greater forces	0.39
F600_07b	Work in a bent, squatting, kneeling position or overhead	0.17
F600_12	Work under noise	0.27
F600_13	Handle microorganisms (pathogens, bacteria, moulds, viruses)	0.13
F605	Working majority of the time outdoors	0.11
F327	Reacting to and solving new problems	0.72
F327_02	Making difficult decisions	0.40
F327_03	Recognizing and closing knowledge gaps	0.36
F327_04	Taking responsibility for others	0.41
F327_05	Convincing and negotiating with others	0.43
F327_06	Communicating with others	0.91
F411_02	Execution of work prescribed in every detail	0.26
F411_03	Repeating same operation in every detail	0.46
F411_04	Confronted with new tasks	0.40
F411_05	Improving existing procedures or trying new things	0.28
F411_13	Working very fast	0.34
F301	Supervising others	0.28

Notes: The table lists survey labels and population averages of the tasks and work conditions considered in the analysis outlined in Section 3.2. Every job characteristic is coded as one if the respondent indicates that it applies *frequently* in her job and zero otherwise. “Supervising others” and “working majority of the working time outdoors” are recorded as binary variables (yes/no) in the survey and coded accordingly in the analysis. Means are computed using population weights. $N = 16,689$.

Table A.5

Determinants of WFH feasibility.

Source: 2018 BIBB/BAuA Employment Survey, weighted, own calculations.

	(1)	(2)	(3)	(4)	(5)
<i>Tasks & work conditions</i>					
Manufacturing, producing goods & commodities (m)	-0.01 (0.02)		-0.00 (0.02)	0.00 (0.02)	0.01 (0.02)
Measuring, testing, quality control (c)	-0.02** (0.01)		-0.03** (0.01)	-0.02 (0.01)	-0.02* (0.01)
Monitoring, control of machines, plants, techn. processes (c)	-0.05*** (0.01)		-0.03** (0.01)	-0.01 (0.01)	-0.00 (0.01)
Repairing, renovating (m)	-0.02 (0.02)		0.00 (0.02)	-0.00 (0.02)	-0.00 (0.02)
Purchasing, procuring, selling (c)	-0.00 (0.01)		0.00 (0.01)	0.02 (0.01)	0.02* (0.01)
Transporting, storing, shipping (m)	-0.06*** (0.01)		-0.04*** (0.01)	-0.00 (0.01)	-0.00 (0.01)

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Table A.5 (continued).

Advertising, Marketing, Public Relations (c)	0.06*** (0.02)	0.07*** (0.02)	0.06*** (0.02)	0.06*** (0.02)
Organizing, planning, preparing work processes (c)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)
Developing, researching, constructing (c)	0.07*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)
Training, instructing, teaching, education (c)	0.03*** (0.01)	0.02 (0.01)	−0.01 (0.01)	−0.01 (0.01)
Gathering information, researching, documenting (c)	0.07*** (0.01)	0.07*** (0.01)	0.05*** (0.01)	0.05*** (0.01)
Providing advice and information (c)	0.05*** (0.01)	0.03*** (0.01)	0.03** (0.01)	0.03** (0.01)
Entertaining, accommodating, preparing food (m)	−0.03 (0.02)	−0.02 (0.02)	−0.03 (0.02)	−0.04* (0.02)
Nursing, caring, healing (m)	−0.07*** (0.02)	−0.08*** (0.02)	−0.03* (0.02)	−0.04** (0.02)
Protecting, guarding, monitoring, regulating traffic (m)	−0.02* (0.01)	−0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
Working with computers (c)	0.14*** (0.01)	0.13*** (0.02)	0.09*** (0.02)	0.09*** (0.02)
Cleaning, waste disposal, recycling (m)	−0.04*** (0.01)	−0.05*** (0.02)	−0.03* (0.01)	−0.03* (0.01)
Work standing up	−0.13*** (0.01)	−0.12*** (0.01)	−0.09*** (0.01)	−0.09*** (0.01)
Lift or carry loads of > 20 kg (men) > 10 kg (women) (m)	−0.04** (0.02)	−0.04** (0.02)	−0.02 (0.02)	−0.02 (0.02)
Exposed to smoke, dust, gases, vapors	−0.04** (0.02)	−0.04* (0.02)	−0.03 (0.02)	−0.02 (0.02)
Work under cold, heat, moisture, humidity, draughts	−0.05*** (0.02)	−0.04** (0.02)	−0.03* (0.02)	−0.03* (0.02)
Work with oil, grease, dirt	−0.02 (0.02)	−0.02 (0.02)	−0.01 (0.02)	−0.01 (0.02)
Manual work that requires high degree of skill (m)	−0.05*** (0.01)	−0.05*** (0.01)	−0.03** (0.01)	−0.03** (0.01)
Work in a bent, squatting, kneeling position or overhead	0.03* (0.02)	0.04** (0.02)	0.02 (0.02)	0.02 (0.02)
Work under noise	−0.04*** (0.01)	−0.05*** (0.01)	−0.05*** (0.01)	−0.05*** (0.01)
Handle microorganisms (m)	−0.04** (0.02)	−0.04** (0.02)	−0.01 (0.02)	−0.01 (0.02)
Working majority of the time outdoors	−0.03 (0.02)	−0.02 (0.02)	0.00 (0.02)	0.00 (0.02)
Reacting to and solving new problems (c)	0.02 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Making difficult decisions (c)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	0.02 (0.01)
Recognizing and closing knowledge gaps (c)	0.03** (0.01)	0.02 (0.01)	0.01 (0.01)	0.01 (0.01)
Taking responsibility for others	−0.03** (0.01)	−0.02* (0.01)	−0.01 (0.01)	−0.02 (0.01)
Convincing and negotiating with others (c)	0.06*** (0.01)	0.05*** (0.01)	0.04*** (0.01)	0.04*** (0.01)
Communicating with others (c)	0.01 (0.02)	0.01 (0.02)	−0.00 (0.02)	−0.01 (0.02)
Execution of work prescribed in every detail	−0.04*** (0.01)	−0.03** (0.01)	−0.02 (0.01)	−0.02* (0.01)
Repeating same operation in every detail	−0.03*** (0.01)	−0.02* (0.01)	−0.02 (0.01)	−0.02 (0.01)
Confronted with new tasks	0.04*** (0.01)	0.03*** (0.01)	0.03*** (0.01)	0.03*** (0.01)
Improving existing procedures or trying new things (c)	0.05*** (0.01)	0.03*** (0.01)	0.03** (0.01)	0.03** (0.01)

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Table A.5 (continued).

Working very fast	–0.00 (0.01)	–0.01 (0.01)	–0.01 (0.01)	–0.01 (0.01)
Supervising others (c)	0.03** (0.01)	0.02* (0.01)	0.04*** (0.01)	0.04*** (0.01)
<i>Worker characteristics</i>				
Female	0.12*** (0.01)	0.05*** (0.01)	0.02* (0.01)	0.01 (0.01)
Migration background	–0.04** (0.02)	–0.02 (0.02)	–0.01 (0.02)	–0.01 (0.02)
Age (x10)	–0.04*** (0.01)	–0.02*** (0.01)	–0.02*** (0.01)	–0.02*** (0.01)
Married	0.00 (0.01)	–0.00 (0.01)	–0.00 (0.01)	0.00 (0.01)
Children under 11	0.00 (0.01)	–0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Academic degree	0.29*** (0.01)	0.10*** (0.01)	0.06*** (0.01)	0.06*** (0.01)
Gross monthly wage in EUR1000	0.07*** (0.00)	0.02*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Weekly contractual working hours (x10)	–0.04*** (0.01)	–0.02*** (0.01)	–0.01 (0.01)	–0.01 (0.01)
Firm tenure in years (x10)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)
Firm with 100+ employees	0.00 (0.01)	–0.02** (0.01)	–0.02* (0.01)	–0.02* (0.01)
R^2	0.30	0.17	0.32	0.36
Observations	16,689	15,678	15,678	15,636
Occupation FE				×
Sector FE				×

Notes: The table reports OLS estimates from regressing WFH feasibility on tasks & working conditions, worker characteristics, occupation fixed effects (2-digit level), and industry fixed effects (21 categories) at the individual level (Eq. (1)). Regressions use survey weights. Standard errors are robust to heteroskedasticity and reported in parentheses.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Table A.6

Variance decomposition of WFH feasibility.

Source: 2018 BIBB/BAuA Employment Survey, own calculations.

$Var(WFH_feasibility_i)$	1.000
$Var(T_i)$	.116
$Var(X_i)$	.009
$Var(\alpha_{o(i)})$	.071
$Var(\alpha_{s(i)})$	.007
$Cov(T_i, \alpha_{o(i)})$	.096
$Cov(X_i, \alpha_{o(i)})$	.018
$Cov(T_i, \alpha_{s(i)})$	.009
$Cov(X_i, \alpha_{s(i)})$	.003
$Cov(\alpha_{s(i)}, \alpha_{o(i)})$	.006
$Cov(T_i, X_i)$	.031
$Var(\varepsilon_i)$	.635
R^2	.365
Observations	15,525

Notes: The table reports the share of variance in individual-level WFH feasibility explained by job tasks and work conditions (T_i), worker characteristics (X_i), 2-digit occupation fixed effects ($\alpha_{o(i)}$), and industry fixed effects ($\alpha_{s(i)}$) based on the regression specified in Eq. (1).

Table A.7

Determinants of untapped WFH.

Source: 2018 BIBB/BAuA Employment Survey, weighted, own calculations.

	Employee-side untapped WFH			Employer-side untapped WFH		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Worker Characteristics</i>						
Female	0.03** (0.02)	0.04*** (0.02)	0.02* (0.02)	0.02 (0.02)	0.03* (0.02)	0.02 (0.02)
Migration background	0.04* (0.02)	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	0.01 (0.02)	0.01 (0.02)
Age (x10)	0.03*** (0.01)	0.01 (0.01)	0.01* (0.01)	-0.01 (0.01)	-0.02*** (0.01)	-0.02** (0.01)
Married	-0.02 (0.02)	-0.01 (0.02)	-0.01 (0.02)	-0.03 (0.02)	-0.02 (0.02)	-0.03* (0.01)
Children under 11	-0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)	0.01 (0.02)	0.01 (0.02)	0.00 (0.01)
Academic degree	-0.17*** (0.01)	-0.08*** (0.02)	-0.06*** (0.02)	-0.22*** (0.02)	-0.13*** (0.02)	-0.09*** (0.02)
Gross monthly wage in EUR1000	-0.05*** (0.00)	-0.03*** (0.00)	-0.03*** (0.00)	-0.07*** (0.00)	-0.05*** (0.00)	-0.05*** (0.00)
Weekly contractual working hours (x10)	0.02** (0.01)	0.03*** (0.01)	0.02* (0.01)	0.08*** (0.01)	0.07*** (0.01)	0.06*** (0.01)
Firm tenure in years (x10)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.02*** (0.01)	0.02*** (0.01)	0.01 (0.01)
Firm with 100+ employees	0.07*** (0.01)	0.06*** (0.01)	0.04*** (0.01)	0.07*** (0.02)	0.04*** (0.01)	0.02 (0.01)
<i>Tasks & work conditions</i>						
Manufacturing, producing goods & commodities (m)		0.03 (0.03)	0.03 (0.03)		0.05* (0.03)	0.04 (0.03)
Measuring, testing, quality control (c)		0.01 (0.01)	0.01 (0.01)		-0.03* (0.02)	-0.03* (0.01)
Monitoring, control of machines, plants, techn. processes (c)		-0.02 (0.02)	-0.02 (0.02)		0.04** (0.02)	0.03 (0.02)
Repairing, renovating (m)		-0.04 (0.03)	-0.02 (0.03)		-0.04* (0.03)	-0.03 (0.02)
Purchasing, procuring, selling (c)		-0.02 (0.02)	-0.01 (0.02)		-0.04* (0.02)	-0.03* (0.02)
Transporting, storing, shipping (m)		-0.00 (0.02)	-0.03 (0.02)		0.00 (0.02)	-0.01 (0.02)
Advertising, Marketing, Public Relations (c)		-0.06*** (0.02)	-0.05*** (0.02)		-0.05** (0.02)	-0.05*** (0.02)
Organizing, planning, preparing work processes (c)		-0.03** (0.02)	-0.03* (0.02)		0.00 (0.02)	0.00 (0.01)
Developing, researching, constructing (c)		-0.05*** (0.02)	-0.03* (0.01)		-0.08*** (0.02)	-0.04** (0.02)
Training, instructing, teaching, education (c)		-0.10*** (0.02)	-0.04** (0.02)		-0.08*** (0.02)	-0.01 (0.02)
Gathering information, researching, documenting (c)		-0.07*** (0.02)	-0.06*** (0.02)		-0.05*** (0.02)	-0.05*** (0.02)
Providing advice and information (c)		-0.05*** (0.02)	-0.05*** (0.02)		-0.06*** (0.02)	-0.06*** (0.02)
Entertaining, accommodating, preparing food (m)		-0.04 (0.03)	-0.03 (0.04)		-0.12*** (0.03)	-0.06* (0.04)
Nursing, caring, healing (m)		0.05** (0.02)	0.04* (0.02)		-0.03 (0.02)	-0.05* (0.03)
Protecting, guarding, monitoring, regulating traffic (m)		-0.02 (0.02)	-0.03 (0.02)		-0.02 (0.02)	-0.02 (0.02)
Working with computers (c)		-0.12*** (0.03)	-0.12*** (0.03)		-0.02 (0.02)	-0.02 (0.02)
Cleaning, waste disposal, recycling (m)		0.01 (0.03)	-0.00 (0.03)		0.02 (0.03)	0.00 (0.02)
Work standing up		-0.01 (0.02)	0.01 (0.02)		-0.02 (0.02)	-0.00 (0.02)

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Table A.7 (continued).

Lift or carry loads of > 20 kg (men) > 410 kg (women) (m)	0.06*	0.04	0.05	0.03		
	(0.03)	(0.03)	(0.03)	(0.03)		
Exposed to smoke, dust, gases, vapors	0.07*	0.05	0.03	0.01		
	(0.04)	(0.04)	(0.03)	(0.03)		
Work under cold, heat, moisture, humidity, draughts	-0.07**	-0.06*	-0.05	-0.03		
	(0.03)	(0.03)	(0.03)	(0.03)		
Work with oil, grease, dirt	0.02	-0.02	0.06*	0.02		
	(0.04)	(0.04)	(0.03)	(0.03)		
Manual work that requires high degree of skill (m)	0.02	0.01	-0.00	-0.01		
	(0.02)	(0.02)	(0.02)	(0.02)		
Work in a bent, squatting, kneeling position or overhead	0.02	0.01	-0.03	-0.03		
	(0.03)	(0.03)	(0.03)	(0.03)		
Work under noise	0.01	0.04	-0.01	0.01		
	(0.02)	(0.02)	(0.02)	(0.02)		
Handle microorganisms (m)	0.01	0.01	0.05*	0.04		
	(0.03)	(0.03)	(0.03)	(0.03)		
Working majority of the time outdoors	-0.05	-0.05	0.02	-0.00		
	(0.04)	(0.04)	(0.03)	(0.04)		
Reacting to and solving new problems (c)	-0.05**	-0.03	0.00	0.01		
	(0.02)	(0.02)	(0.02)	(0.02)		
Making difficult decisions (c)	0.01	-0.00	-0.02	-0.03**		
	(0.01)	(0.01)	(0.02)	(0.01)		
Recognizing and closing knowledge gaps (c)	-0.00	0.00	-0.04***	-0.03*		
	(0.01)	(0.01)	(0.02)	(0.01)		
Taking responsibility for others	-0.01	-0.00	-0.00	0.01		
	(0.02)	(0.02)	(0.02)	(0.02)		
Convincing and negotiating with others (c)	-0.03**	-0.04**	-0.04**	-0.05***		
	(0.02)	(0.02)	(0.02)	(0.02)		
Communicating with others (c)	-0.13***	-0.13***	-0.04	-0.05*		
	(0.04)	(0.03)	(0.03)	(0.03)		
Execution of work prescribed in every detail	0.11***	0.09***	0.15***	0.12***		
	(0.02)	(0.02)	(0.02)	(0.02)		
Repeating same operation in every detail	0.02	0.02	0.08***	0.07***		
	(0.02)	(0.02)	(0.02)	(0.02)		
Confronted with new tasks	-0.01	-0.02	-0.03*	-0.03**		
	(0.01)	(0.01)	(0.02)	(0.01)		
Improving existing procedures or trying new things (c)	-0.03**	-0.02	-0.02	-0.00		
	(0.01)	(0.01)	(0.02)	(0.02)		
Working very fast	0.02	0.01	0.02	0.01		
	(0.01)	(0.01)	(0.02)	(0.01)		
Supervising others (c)	-0.01	-0.04***	-0.03	-0.05***		
	(0.02)	(0.02)	(0.02)	(0.02)		
R ²	0.11	0.23	0.27	0.15	0.24	0.30
Observations	7,272	7,272	7,204	8,981	8,981	8,903
Occupation FE			×			×
Sector FE			×			×

Notes: The table reports OLS estimates from regressing untapped WFH on tasks & working conditions, worker characteristics, occupation fixed effects (2-digit level), and industry fixed effects (21 categories) at the individual level. The sample is restricted to employees with a WFH feasible job. Employee-side untapped WFH is equal to one if the respondent never works from home and would not accept an offer to work from home, and zero otherwise. Employer-side untapped WFH is equal to one if the respondent never works from home and would accept an offer to WFH, and zero otherwise. Regressions use survey weights. Standard errors are robust to heteroskedasticity and reported in parentheses.

*** $p < 0.01$.

** $p < 0.05$.

* $p < 0.1$.

Table A.8

Capacity to work from home by sector.

Source: 2018 BIBB/BAuA Employment Survey, Employment Statistics of the Federal Employment Agency (BA) 2019, own calculations.

NACE main sections	Frequent WFH	Occasional WFH	Untapped WFH (employer)	Untapped WFH (employee)	WFH capacity
Overall	9.328	16.27	20.32	9.604	55.52
A Agriculture, Forestry and Fishing	7.066	8.811	13.64	7.790	37.31
B Mining and Quarrying	5.054	12.54	17.05	6.350	41.00
C Manufacturing	7.153	15.29	20.87	9.304	52.62
D Electricity, Gas, Steam and Air Conditioning Supply	11.10	22.65	24.69	9.991	68.43
E Water Supply; Sewerage, Waste Management and Remediation Activities	6.199	13.60	18.30	7.747	45.85
F Construction	4.865	12.08	17.48	7.202	41.62
G Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles	8.073	14.22	21.37	9.348	53.02
H Transportation and Storage	5.245	9.002	15.80	7.299	37.35
I Accommodation and Food Service Activities	8.789	9.817	12.84	8.621	40.06
J Information and Communication	17.89	35.34	22.26	9.271	84.76
K Financial and Insurance Activities	11.85	25.78	36.65	14.94	89.22
L Real Estate Activities	13.71	22.43	24.76	10.03	70.93
M Professional, Scientific and Technical Activities	12.50	24.36	27.59	11.67	76.12
N Administrative and Support Service Activities	7.732	12.39	17.43	10.05	47.60
O Public Administration and Defence; Compulsory Social Security	10.76	19.81	25.75	12.94	69.26
P Education	30.20	20.94	13.98	7.359	72.49
Q Human Health and Social Work Activities	6.762	13.97	17.46	9.638	47.83
R Arts, Entertainment and Recreation	16.60	18.87	17.21	7.214	59.89
S Other Service Activities	11.39	17.62	18.92	10.65	58.59
T Activities of Households as Employers; Household Production for Own Use	10.73	18.19	15.68	9.867	54.47
U Activities of Extraterritorial Organisations and Bodies	9.763	18.75	23.92	10.69	63.11

Notes: The figure displays WFH capacities and pre-pandemic WFH take-up overall and by sector (NACE main sections).

Table A.9

Capacity to work from home by industry.

Source: 2018 BIBB/BAuA Employment Survey, Employment Statistics of the Federal Employment Agency (BA) 2019, own calculations.

NACE 2-digit industries	Frequent WFH	Occasional WFH	Untapped WFH (employer)	Untapped WFH (employee)	WFH capacity
Overall	9.328	16.27	20.32	9.604	55.52
Crop and animal production, hunting and related service activities	7.010	8.701	13.61	7.830	37.15
Forestry and logging	7.676	10.02	13.98	7.428	39.10
Fishing and aquaculture	7.353	9.333	13.98	6.939	37.61
Mining of coal and lignite	4.655	12.93	16.67	5.120	39.38
Extraction of crude petroleum and natural gas	7.886	17.91	20.23	7.101	53.13
Mining of metal ores	4.528	11.42	17.36	5.959	39.27
Other mining and quarrying	4.747	11.58	16.35	6.340	39.01
Mining support service activities	5.761	14.05	18.86	7.392	46.06
Manufacture of food products	6.066	10.93	16.93	7.909	41.83
Manufacture of beverages	8.632	14.09	18.43	8.260	49.41
Manufacture of tobacco products	8.470	15.92	20.64	9.534	54.56
Manufacture of textiles	7.039	16.21	24.32	10.34	57.91
Manufacture of wearing apparel	9.876	19.65	25.28	10.61	65.42
Manufacture of leather and related products	6.693	16.10	24.64	10.37	57.80
Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	5.076	10.47	16.24	11.04	42.82
Manufacture of paper and paper products	6.625	16.29	25.51	10.16	58.59
Printing and reproduction of recorded media	7.358	18.14	27.41	10.50	63.42
Manufacture of coke and refined petroleum products	8.507	19.61	23.76	9.369	61.24
Manufacture of chemicals and chemical products	8.227	19.15	23.52	9.895	60.79
Manufacture of pharmaceuticals, medicinal chemical and botanical products	8.608	20.11	23.86	10.02	62.59
Manufacture of rubber and plastics products	5.890	12.74	18.62	11.03	48.28
Manufacture of other non-metallic mineral products	5.984	13.31	17.99	6.323	43.61
Manufacture of basic metals	5.055	11.51	18.99	7.810	43.36
Manufacture of fabricated metal products, except machinery and equipment	5.144	11.33	18.95	7.915	43.33
Manufacture of computer, electronic and optical products	10.43	21.54	23.20	9.562	64.73

(continued on next page)

Table A.9 (continued).

Manufacture of electrical equipment	9.409	19.34	22.94	9.605	61.29
Manufacture of machinery and equipment n.e.c.	7.836	16.38	21.74	9.399	55.36
Manufacture of motor vehicles, trailers and semi-trailers	7.034	16.17	21.86	10.05	55.12
Manufacture of other transport equipment	7.938	17.44	22.17	10.02	57.57
Manufacture of furniture	5.662	11.26	17.24	11.42	45.58
Other manufacturing	8.129	15.70	20.70	9.756	54.29
Repair and installation of machinery and equipment	7.953	16.53	21.57	9.588	55.64
Electricity, gas, steam and air conditioning supply	11.10	22.65	24.69	9.991	68.43
Water collection, treatment and supply	8.383	18.91	22.53	9.007	58.83
Sewerage	6.598	15.52	19.90	8.190	50.21
Waste collection, treatment and disposal activities; materials recovery	5.656	12.13	17.13	7.398	42.31
Remediation activities and other waste management services	7.010	14.69	18.32	8.062	48.08
Construction of buildings	4.375	11.41	17.91	6.980	40.68
Civil engineering	3.884	10.45	17.15	6.737	38.22
Specialized construction activities	5.135	12.50	17.43	7.328	42.39
Wholesale and retail trade and repair of motor vehicles and motorcycles	7.000	13.52	21.04	10.54	52.10
Wholesale trade, except of motor vehicles and motorcycles	12.57	19.33	22.82	9.340	64.06
Retail trade, except of motor vehicles and motorcycles	5.751	11.44	20.62	9.027	46.84
Land transport and transport via pipelines	3.917	7.350	12.49	6.100	29.85
Water transport	8.084	13.82	18.84	8.718	49.46
Air transport	6.696	10.31	17.98	8.055	43.04
Warehousing and support activities for transportation	6.186	10.66	17.85	8.033	42.73
Postal and courier activities	5.342	7.973	17.37	7.856	38.54
Accommodation	9.913	10.52	13.07	9.267	42.77
Food and beverage service activities	8.339	9.535	12.74	8.363	38.98
Publishing activities	16.74	30.50	26.10	10.29	83.62
Motion picture, video and television programme production, sound recording and music publishing activities	15.96	26.41	19.66	7.806	69.84
Programming and broadcasting activities	17.71	29.05	24.13	8.879	79.77
Telecommunications	13.28	26.30	24.32	9.589	73.49
Computer programming, consultancy and related activities	18.72	38.49	21.13	9.079	87.43
Information service activities	16.64	30.32	24.94	10.27	82.17
Financial service activities, except insurance and pension funding	11.20	25.22	37.66	15.35	89.43
Insurance, reinsurance and pension funding, except compulsory social security	12.43	26.56	35.92	14.63	89.55
Activities auxiliary to financial service and insurance activities	13.50	26.97	33.91	13.84	88.21
Real estate activities	13.71	22.43	24.76	10.03	70.93
Legal and accounting activities	10.88	24.03	36.49	16.20	87.59
Activities of head offices; management consultancy activities	13.89	26.00	25.62	11.02	76.53
Architectural and engineering activities; technical testing and analysis	10.19	23.69	26.30	10.51	70.69
Scientific research and development	17.48	22.55	21.44	9.091	70.56
Advertising and market research	14.57	26.63	26.59	10.29	78.08
Other professional, scientific and technical activities	12.20	22.58	25.68	10.34	70.79
Veterinary activities	3.938	11.98	18.61	9.094	43.62
Rental and leasing activities	11.24	18.20	21.15	9.403	59.98
Employment activities	6.010	11.47	18.29	8.604	44.37
Travel agency, tour operator, reservation service and related activities	12.18	15.85	17.70	9.907	55.64
Security and investigation activities	5.751	11.46	21.14	4.281	42.63
Services to buildings and landscape activities	6.180	7.314	11.99	12.67	38.15
Office administrative, office support and other business support activities	13.64	23.35	24.55	10.31	71.86
Public administration and defence; compulsory social security	10.76	19.81	25.75	12.94	69.26
Education	30.20	20.94	13.98	7.359	72.49
Human health activities	5.153	12.62	18.62	9.369	45.77
Residential care activities	7.853	14.51	15.25	9.973	47.59
Social work activities without accommodation	9.233	16.39	16.95	9.912	52.48
Creative, arts and entertainment activities	16.84	25.72	15.37	5.567	63.51
Libraries, archives, museums and other cultural activities	13.38	18.96	22.93	10.67	65.94
Gambling and betting activities	8.159	13.45	19.93	6.196	47.74
Sports activities and amusement and recreation activities	21.18	17.51	15.35	7.576	61.61
Activities of membership organizations	15.40	22.21	21.57	10.79	69.98
Repair of computers and personal and household goods	9.170	18.64	22.18	9.560	59.55
Other personal service activities	5.735	10.78	14.69	10.55	41.76
Activities of households as employers of domestic personnel	10.81	18.29	15.67	9.907	54.68
Undifferentiated goods- and services-producing activities of private households for own use	5.499	11.85	15.98	7.290	40.62
Activities of extraterritorial organizations and bodies	9.763	18.75	23.92	10.69	63.11

Notes: The figure displays WFH capacities and pre-pandemic WFH take-up by industry (NACE 2-digit).

Table A.10

Replicating DN's task-exclusion WFH measure with the 2018 BIBB/BAuA survey.

-
- If respondents report any of the following as true, we code their job as not feasible with full-time WFH:
- Never using the Internet or E-Mail processing
 - Frequently lifting or carrying loads of more than 10 kg (women) or 20 kg (men)
 - Frequent exposure to smoke, dust, gases, or vapor
 - Frequent exposure to cold, heat, moisture, humidity, or draughts
 - Frequently handling microorganisms such as pathogens, bacteria, molds or viruses
 - Frequently working with oil, grease, or dirt
 - Works the majority of time outdoors
 - Frequently repairing or renovating
 - Frequently protecting, guarding, monitoring, or regulating traffic
 - Frequently cleaning, disposing of waste, or recycling
 - Frequently monitoring or controlling machines, plants, or technical processes
-

Notes: The table describes the replication of [Dingel and Neiman's \(2020\)](#) WFH feasibility index using individual-level task information from the 2018 BIBB/BAuA Employment Survey. The original measure uses O*NET data; in particular, an occupation is defined as one that cannot be performed from home if at least of the following conditions are met: Average respondent says they use email less than once per month; Average respondent says they deal with violent people at least once a week; Majority of respondents say they work outdoors every day; Average respondent says they are exposed to diseases or infection at least once a week; Average respondent says they are exposed to minor burns, cuts, bites, or stings at least once a week; Average respondent says they spent the majority of time walking or running; Average respondent says they spent the majority of time wearing common or specialized protective or safety equipment. Performing General Physical Activities is very important; Handling and Moving Objects is very important; Controlling Machines and Processes [not computers nor vehicles] is very important; Operating Vehicles, Mechanized Devices, or Equipment is very important; Performing for or Working Directly with the Public is very important; Repairing and Maintaining Mechanical Equipment is very important; Repairing and Maintaining Electronic Equipment is very important; Inspecting Equipment, Structures, or Materials is very important.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.euroecorev.2022.104354>.

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