Work from Home and Health-Related Absenteeism

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Work in progress – Please do not cite

March 26, 2026

Abstract

We study the effect of working from home (WFH) on health-related absenteeism. We draw on a monthly panel (2018–2023) of nearly 1.9 million workers insured under a major German statutory health insurance fund. Our identification strategy leverages the differential exposure to the unexpected shift to WFH in 2020, resulting in about one-quarter of German employees regularly working remotely today. Specifically, our difference-in-differences design compares sick leave take-up across workers with different *WFH potential*, i.e., the teleworkability of their occupation in February 2020. Our results imply a nontrivial lasting response to WFH. Compared to the pre-treatment mean, the monthly likelihood of sick leave take-up declined by 3.3% by 2023 due to a 10-percentage-point increase in WFH potential (comparable to a shift from performing and entertainment professions to media documentation and information services). These effects are driven by reductions in respiratory infections and musculoskeletal disorders, such as back pain. The response reflects not only behavioral changes in sick leave take-up, but also genuine health improvements.

Keywords: Remote Work, Absenteeism, Sickness Absence, Sick Leave, Health

JEL Codes: I10, J22

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1 Introduction

Health-related absenteeism imposes a massive economic burden. In Germany, sick days have risen by nearly 40% since 2019, causing an estimated EUR 227 billion loss in gross value added (5.8% of GVA) in 2024 (BAuA, 2024). Over the same period, the mass experiment in working from home (WFH) triggered a lasting transformation of work environments (Barrero *et al.*, 2023): today, a quarter of employees regularly work remotely, placing Germany among the world's high-WFH countries, alongside the US and the UK (Alipour *et al.*, 2025; Zarate *et al.*, 2024; Aksoy *et al.*, 2025).[1] Yet despite these conspicuous trends in WFH and absenteeism, evidence for a causal relationship or the mechanisms at work remains scarce.

This paper studies the causal impact of WFH on sickness absenteeism in Germany. The analysis builds on a monthly panel of 1.9 million workers insured under a major statutory health fund from 2018 to 2023. Our identification strategy exploits the differential exposure to the WFH shock induced by the Covid-19 pandemic as a natural experiment that permanently unlocked previously unused WFH opportunities. We measure the pre-treatment WFH potential of a worker's occupation shortly before the pandemic and study the subsequent responses to the WFH potential in granular health insurance data.[2] Specifically, we use a difference-in-differences (DiD) design that compares absenteeism across individuals with different WFH potential over time. The rich data allow us to recover the intention-to-treat (ITT) effects of WFH on absences by diagnosis and to study heterogeneity by age and gender. Our key finding is that WFH exposure persistently reduces absenteeism in the post-Covid economy, reflecting both behavioral changes and genuine health improvements.

The impact of WFH on health-related absenteeism is ambiguous ex ante. WFH can directly improve health by reducing exposure to contagious diseases from co-workers, as documented for the Coronavirus (Alipour *et al.*, 2021). But WFH may also worsen health through poor ergonomics, prolonged sitting, limited movement, and fewer social interactions (Nguyen, 2023; Morton *et al.*, 2024). The flexibility of WFH further incentivizes behavioral changes: workers can continue working while sick (actual presenteeism) or more easily pretend to do so (fake presenteeism). Parents might use WFH to manage caregiving emergencies without taking leave, with mixed implications for gender inequalities in (un)paid work and leisure (Goldin, 2022; von Gaudecker *et al.*, 2024; Alipour, 2025). Remote work can also facilitate medical visits during work hours, potentially leading to an increase in the number of diagnoses. Finally, WFH may intensify competitive pressures among workers because employers can hire from a

[1] For example, in 2024/2025, German college and university graduates worked from home an average of 1.6 days per week(Aksoy *et al.*, 2025); a similar number to the US and slightly below the UK (1.8) and Canadian (1.9) levels.

[2] We use the WFH potential measure for Germany from Alipour *et al.* (2023), which corresponds to the fraction of individuals within each 3-digit occupational code who reported in 2018 that their job *could* be done from home at least partly.

larger applicant pool (Barrero *et al.*, 2021, 2023; Bloom *et al.*, 2024), which could discourage sick leave.

In sum, WFH may substitute for sick leave, change reporting behavior, or affect health directly. Our baseline estimates capture all channels. However, the richness of our data also enables us to isolate diagnoses where behavioral and health mechanisms differ. Importantly, because every formal sick day incurs costs, our estimates remain policy-relevant even without fully disentangling these mechanisms.

We show four sets of results. First, we find that individuals in jobs with higher WFH potential are significantly less likely to take up sick leave. The effects emerge immediately in February 2020 and remain persistent. Even study evidence shows that they are stronger during the two lockdowns, and more generally, in each year's winter months. After the end of the public health emergency, starting in Summer 2022, the effect stabilizes. By the end of 2023, a 10-percentage-point increase in WFH potential triggers a 0.4-percentage-point decrease in sick leave porbability. This corresponds to a 3.3% decline relative to the pre-treatment mean, suggesting a sizable effect. Intuitively, a 10-percentage-point increase in WFH potential corresponds, for instance, to a shift from performing and entertainment professions to media documentation and information services.

Second, we break down the average effect by diagnosis and leave duration. Concentrating on the most frequent ICD-10 groups, we find the largest reductions in sick leave due to musculoskeletal disorders (7.9%), which might indicate in parts a greater scope to adjust work arrangements. This pattern aligns with the largest reductions occurring for absences of more than 26 days (6.9%), as musculoskeletal disorders are associated with the longest spells of sick leave. However, we also find substantial reductions in sick leave due to infectious and parasitic diseases (4.6%), which might indicate a reduced contagion when working from home. Correspondingly, shorter absences decline by between 3.3% and 4.9%. On average, a 10-percentage-point increase in WFH potential reduces the monthly number of sick days by 4.5% relative to the pre-treatment mean.

Third, to inquire both the health channel (via infectious and respiratory diseases) and the behavioral channel (via musculoskeletal disorders) more deeply, we analyze doctor visits and hospitalizations. While doctoral visits can become more frequent for workers with higher flexibility in the workplace, hospitalizations reflect more severe health conditions. A negative estimate on all doctoral visits suggests an overall health improvement from WFH and some substitution from sick leaves to diagnosis without a certificate. The effect declines to a reduction of 0.6% for a 10 p.p. increase in WFH potential, which is about one fifth of the sick leave effect. Similarly, the health channel is supported by a reduction in hospitalizations. The effect reduces by 1.3%

Finally, in terms of heterogeneity, there is a clear age gradient: the absenteeism-reducing effect of WFH decreases with age, which is driven by men. However, we generally find that women's

sick leave behavior is slightly more responsive to WFH opportunities. Gender differences are most pronounced between the ages of 36 and 50 when dual caregiving obligations (for children and elderly parents) are common, and the gender difference in time spent on unpaid care work is largest (Schäper *et al.*, 2023). We show that these patterns do not reflect differences in the actual WFH uptake.

The validity of our DiD estimates is supported by the absence of pretrends. Our results are robust to comparing individuals within the same state, age group, gender, education, or industry, and to alternative definitions of sickness absence. Moreover, the effect is not driven by Covid-19 as effects for group U are small and short-lived.

Our findings indicate that sustained WFH adoption reduces absenteeism, which has important policy implications. Importantly, the literature converges on neutral to positive productivity effects of WFH at both the micro and the macro level (Aksoy *et al.*, 2025; Bloom *et al.*, 2024; Boeri *et al.*, 2024; Choudhury *et al.*, 2024; Angelici and Profeta, 2023; Fenizia and Kirchmaier, 2024; Barrero *et al.*, 2021; Bloom *et al.*, 2015). This implies that reductions in formal sick leave generate genuine welfare gains rather than merely shifting costs to lower productivity (i.e., by incentivizing working while sick). A back-of-the-envelope calculation illustrates the aggregate relevance of our findings: given the occupational structure of the German economy, where the average job had a WFH potential of 0.58 in February 2020, our DiD estimates imply that the realization of previously latent WFH opportunities lowers the aggregate risk of a monthly sick absence by about 2.4 p.p. or 19% relative to the pre-pandemic mean.

This paper contributes to several strands of literature. First, we speak to the well-established literature on the determinants of sickness absence. Among the leading causes of health-related absenteeism, this research has mostly focused on the role of individual health (Paringer, 1983), job satisfaction (Diestel *et al.*, 2014), personal and family-related issues (Allen, 1981), employment protection (Ichino and Riphahn, 2005), sick leave policies (De Paola *et al.*, 2014), and workplace environment, such as exposure to noise or dust (Ose, 2005). Several studies note that discouraging absence can create costs by inducing presenteeism (working while sick), which slows recovery (Gilleskie, 1998) and bears the risk of spreading contagious diseases at the workplace (Barmby and Larguem, 2009; Pichler and Ziebarth, 2019).[3] We contribute to this discussion by providing causal evidence on the absenteeism responses to the large-scale shift to remote work.

Second, we contribute to the limited and conflicting evidence on the effect of WFH on sickness absence and health. Early correlational studies find that WFH options are associated with lower absenteeism (Allen, 1981; Dionne and Dostie, 2007). This has been confirmed in a randomized field experiment in a Chinese call center (Bloom *et al.*, 2015) and is consistent with other experimental evidence that WFH improves job satisfaction (Bloom *et al.*, 2024; Choud-

[3]Consistent with this argument, during the Covid pandemic, German counties where workers could more easily switch to WFH experienced fewer Covid infections and deaths (Alipour *et al.*, 2021).

hury *et al.*, 2024). Quasi-experimental studies typically rely on self-reported health and yield mixed results. Goux and Maurin (2025) find negative health effects of a French reform that facilitated access to WFH, especially for men. They argue that WFH increases pathologies linked to an overly sedentary lifestyle for men. In contrast, Costi *et al.* (2024) document no effect of an Italian return-to-office mandate on well-being or mental health among public sector employees. Evidence on mental health effects is similarly conflicting (Nguyen, 2023; Botha *et al.*, 2026a).[4] A distinct aspect of our study is that we combine a bold natural experiment that unexpectedly shifted millions of workers into remote work with registry data on health care use and diagnoses to identify the effect of WFH on sickness absenteeism.[5]

Finally, our findings that women's sickness absence is more responsive to WFH opportunities than men's to the current discussion of the potentially gendered effects of WFH and its implications for gender inequality in labor market outcomes. While it has been often argued that improving remote work opportunities can help women balance work and care responsibilities or engage man more in unpaid work, thereby reducing gender gaps (Bertrand, 2018; Olivetti *et al.*, 2024; von Gaudecker *et al.*, 2024), there is little consensus on this issue thus far. In contrast, opposing voices have argued that WFH can exacerbate gender disparities, particularly through its reinforcement of traditional roles in paid and unpaid work (Alipour, 2025). While this debate has so far concentrated on employment, wages, and the division of non-work time within couples, we show that differential responses to WFH along the absenteeism and health margins may also constitute an important channel through which WFH shapes gender gaps.

The paper proceeds with a description of the institutional background and our data in Section 2. Section 3 presents the empirical strategy and identifying assumptions. Section 4 shows the main results. Section 5 explores potential mechanisms and reveals heterogeneity by age and gender. Section 6 concludes.

2 Background and data

2.1 Sick leave in Germany

Health insurance system. Health insurance in Germany is mandatory and provided through both statutory and private systems. Nearly 90% of the population is covered by statutory health insurance, while individuals with incomes above a certain threshold or in specific occupations (e.g., self-employed, civil servants) may opt for private health insurance. Statutory health insurance covers extensive medical services uniformly across enrollees. Private health

[4] Botha *et al.* (2026b) find large positive mental-health effects of WFH for women in Australia but no effects for men. Nguyen (2023) reports negative effects during the pandemic using a Roy selection model for the UK, driven primarily by loneliness. Using Brazilian records of paid sick leave, Mancha and Peres (2024) find a substantial increase in leaves related to mental health issues among men.

[5] Related research studies remote instruction during the pandemic. For instance, Björkegren *et al.* (2024) find that students in Sweden experienced fewer diagnoses and prescriptions for depression and anxiety after instruction moved online.

insurance typically offers equivalent or superior coverage (for more details, see e.g., OECD and European Observatory on Health Systems and Policies, 2023).

Sick leave regulations. Employees must notify their employer if they are unable to work due to illness, typically on the first day of absence. By law, a medical certificate of incapacity (*Arbeitsunfähigkeitsbescheinigung*, AU) is required from the fourth day of absence, though employers may request one earlier.[6] Importantly, physicians issue AUs as a binary determination of work capacity: unlike the Dutch or Nordic system, Germany has no option for partial sick leaves.

Benefits. Germany provides extensive employee protection during illness. Employers must continue wage payments for up to six weeks per illness episode.[7] Thereafter, the insurance pays sickness benefits equal to 70% of the gross wage, capped at 90% of the net wage, for up to 78 weeks. A gradual, part-time return to work (*stufenweise Wiedereingliederung*) is possible during this period. Employees are legally protected against dismissal solely due to illness, may reclaim vacation days lost to illness, and can take leave to care for a child under the age of 12 who is sick.

2.2 Health Insurance Data

We utilize registry data from one of Germany's largest statutory health insurers, which currently covers more than 8 million individuals nationwide and has a budget exceeding € 50 billion. Germany has 93 different statutory health insurance firms (01/2026), mostly due to historical reasons, as health insurers were historically tied to specific industries. This results in some differences in the socio-demographics of members across insurers, although people have been able to switch between insurance plans freely since 1996. For example, the share of women in our data is 57.1% (Table B.1), which is higher than the share in statutory health insurance (51.6%) or the general population (50.6%) (BMG, 2025; DESTATIS, 2025). The reason is, for example, that men are more frequently members in private insurance given their higher income and higher share of self-employment status. They are also more often member of public insurance focusing on engineers and technicians. Therefore, we cannot claim that our data is perfectly representative of the general population.

We gained access to individual-level outpatient data on sickness absence and diagnoses, as well as any visits to physicians and hospitalizations. The records include detailed information on sick leave and hospitalization dates. The diagnoses are classified using the ICD-10-GM

[6] During the Covid-19 pandemic, employees with mild illnesses could temporarily obtain an AU by telephone. Until 2022, employees had to submit paper certificates to employers and insurers. Since 2023, physicians transmit AUs electronically. Our data include all absences filed with an AU.

[7] This obligation is stipulated in the *Entgeltfortzahlungsgesetz* (Act on Continued Remuneration). Each new, unrelated illness triggers a new six-week period.

coding system.[8] In addition, the data include sociodemographic characteristics such as year of birth, gender, place of residence, insurance status (e.g., due to employment), and occupation classified according to the German Classification of Occupations (KldB 2010).

We restrict the sample to individuals of prime working age (26–55) who were employed on February 15, 2020, just before the first stay-at-home order in Germany. We focus on employees subject to mandatory social security contributions, who constitute about 75% of the working population.[9] And exclude individuals who were not insured throughout our observation period.[10] The health insurance records cover January 2018 to December 2023, allowing us to study sickness absence up to two years before and four years after the WFH shock. We convert daily sick-leave records into a monthly panel. Our main outcome is an indicator for having a sick leave spell in a given month. However, we also present results for the number of sick days per month and indicators of sick leave by diagnosis and duration of absence, as well as any visits to physicians without sick leave notification. The final sample consists of a balanced panel of 1,867,637 individuals whom we follow for 72 months. Table B.1 reports summary statistics. Our sample is roughly similar to the population benchmark across age groups and occupational structure, with a slight overrepresentation of women in the insurance data (Table B.2).

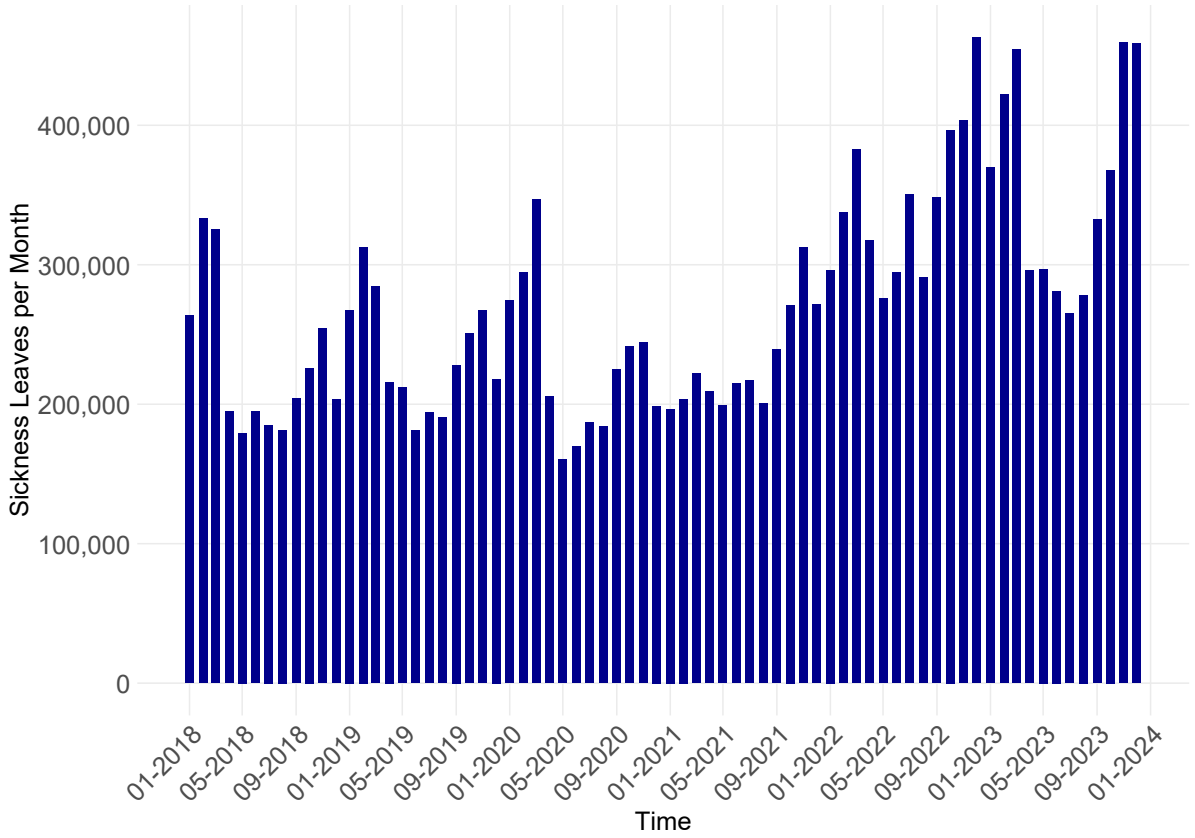
In 2019, an average of 12% of workers experienced at least one sickness-absence day per month. This rate remained stable in 2020 and 2021 but rose to about 19% in 2022 and 2023. Sickness absence follows a pronounced seasonal pattern, with peaks in fall and winter that mirror typical flu and cold waves (Figure 1). Across months, between 8% and 24% of individuals register at least one day of sickness absence.

[8] The ICD-10-GM is the German modification of the International Statistical Classification of Diseases and Related Health Problems, maintained by the World Health Organization.

[9] Specifically, we focus on employees who are fully insured in all branches of social insurance, i.e., health, long-term care, pension, and unemployment insurance. We exclude marginal employment (*Minijobs*), which refers to subsidized low-earning jobs below a monthly income threshold (520 euros until the end of 2023), and self-employment, which is not subject to social insurance. For more details, see e.g., Collischon *et al.* (2025).

[10] For some individuals, we observe gaps in their insurance status, resulting in missing information on the outcomes. We tested whether treatment affected the probability of being insured throughout the analysis period and found no evidence of selection into the sample.

Figure 1: Number of Individuals on Sick Leave per Month between 2018 and 2023



Notes: The figure shows the monthly number of individuals with at least one day of sickness absence within the month. The sample comprises a balanced panel of individuals aged 26–55 and employed on February 15, 2020.

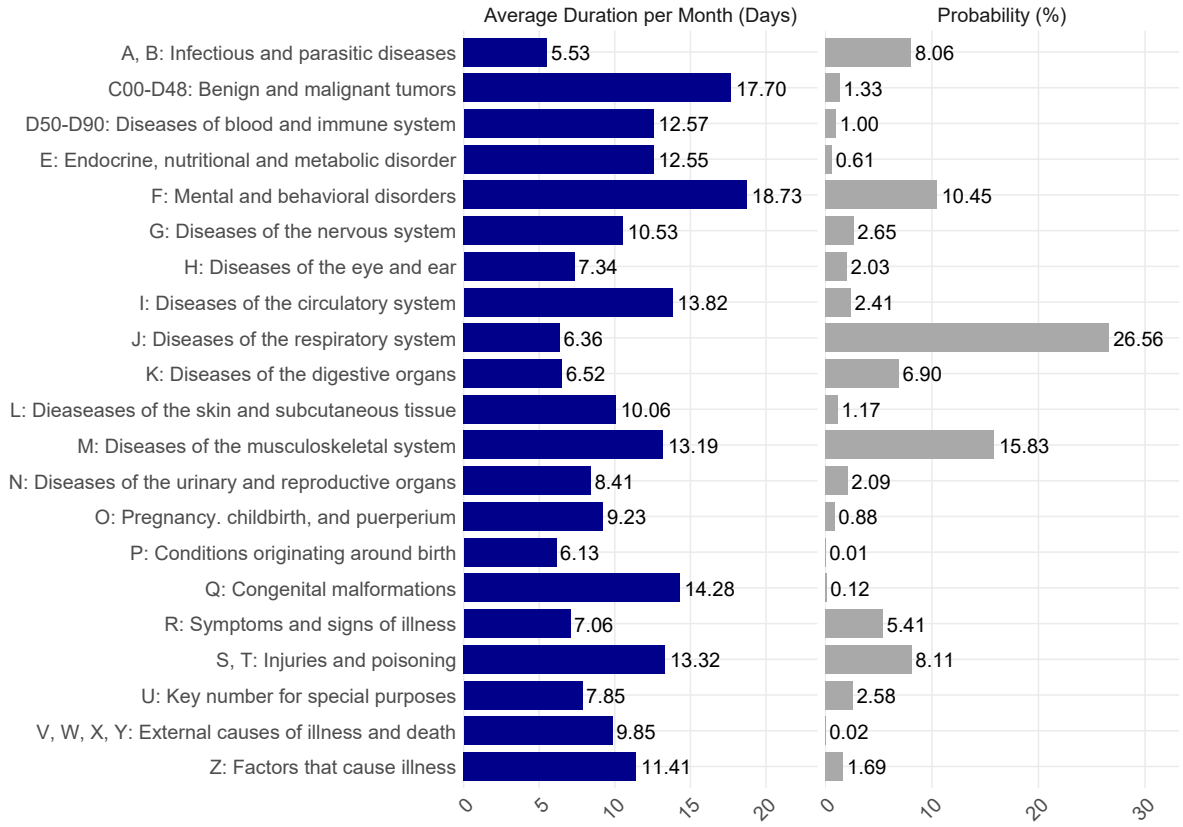
In terms of absence length, the average number of sick leave days in a given calendar month increased from 1.2 in 2018 to 1.9 per individual (see Table B.1). However, conditional on sick leave take up in a given month, more than half of sick leave spells are for fewer than five days, i.e., one workweek (see Appendix Figure C.3), with an additional mass point at 12 days (two workweeks). The bunching at 30 and 31 days is due to the truncation of durations at the end of the month.[11]

Figure 2 reports the distribution of ICD-10 diagnoses across sick-leave certificates between 2018 and 2023. Sickness absence is dominated by respiratory diseases (J, 26.5%), followed by musculoskeletal disorders (M, 16%), and mental and behavioral disorders (F, 10%), with injuries (S–T, 8.1%), infectious diseases (A–B, 8%), and digestive system diseases (K, 6.9%) accounting for smaller shares.[12]

[11] Fewer than 1.5% of certificates exceed one month. Current law requires a new AU for each month of illness but physicians may certify expected duration and issue follow-up AUs if the illness persists.

[12] Special purposes (U), include the codes *U7.1* and *U7.2*, which were used for Covid-19 diagnosis. Prior to the pandemic, the U category was used only rarely.

Figure 2: Sick Leaves by ICD-10 Diagnosis, 2018–2023



Notes: The figure shows the distribution of ICD-10 diagnosis (chapter level) across sick-leave certificates (*Arbeitsunfähigkeitsbescheinigung* - AU) over our observation period (2018–2023). Sample restricted to individuals aged 26–55 and employed on February 15, 2020.

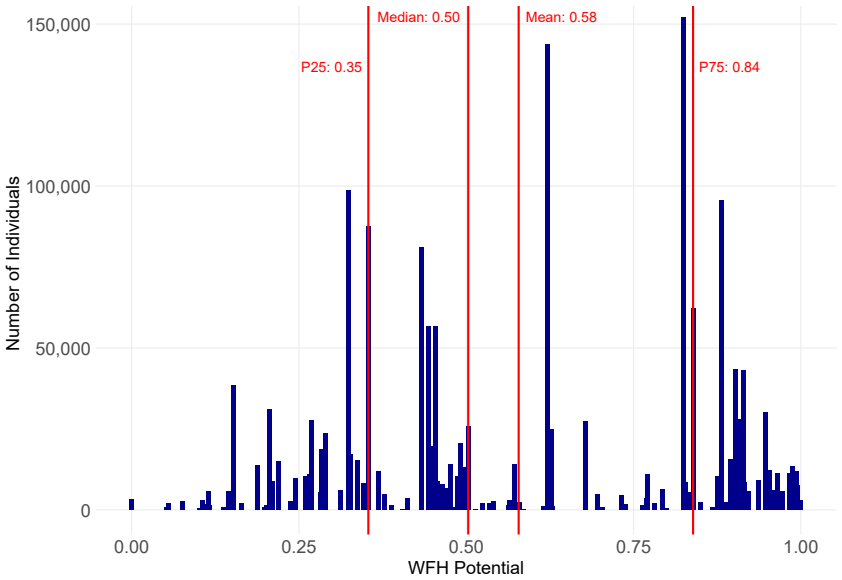
2.3 Exposure to the WFH shock

WFH potential. We capture individuals' exposure to the WFH shock by the *WFH potential* of their occupation shortly before the pandemic (February 2020). We use the measure proposed by Alipour *et al.* (2023), which is derived from the 2018 BIBB-BAuA Employment Survey (Hall *et al.*, 2020). Specifically, WFH potential corresponds to the fraction of individuals in each KldB 3-digit occupation (136 categories) who report that their job *could* be done from home at least partly.

Figure 3 plots a histogram of WFH potential (scaled from 0 to 1) for the 1,867,637 individuals in our estimation sample. The mean is 0.58, implying that 58% of sampled employees could have performed part of their job remotely before the pandemic. This closely matches the corresponding estimate in the BIBB-BAuA sample (0.59). For reference, the mean WFH potential corresponds to jobs in textile and leather occupations or performing and entertainment professions. The median employee works in non-medical therapy and healing practices, with a WFH potential of 0.50.

The distribution of WFH potential shows substantial dispersion: the interquartile range spans from 0.35 (logistics and warehousing) to 0.84 (law and administrative professions). An important portion of the heterogeneity arises *within* 1-digit occupations (9 groups); see Appendix Figure C.2. This feature is relevant as it allows us to assess how sensitive our results are to restricting comparisons to workers within the same broad occupation; thus, mitigating concerns that occupation-level shocks drive the estimated impact of WFH exposure on absenteeism.

Figure 3: Distribution of WFH Potential



Notes: The figure shows the distribution of WFH potential [0, 1].

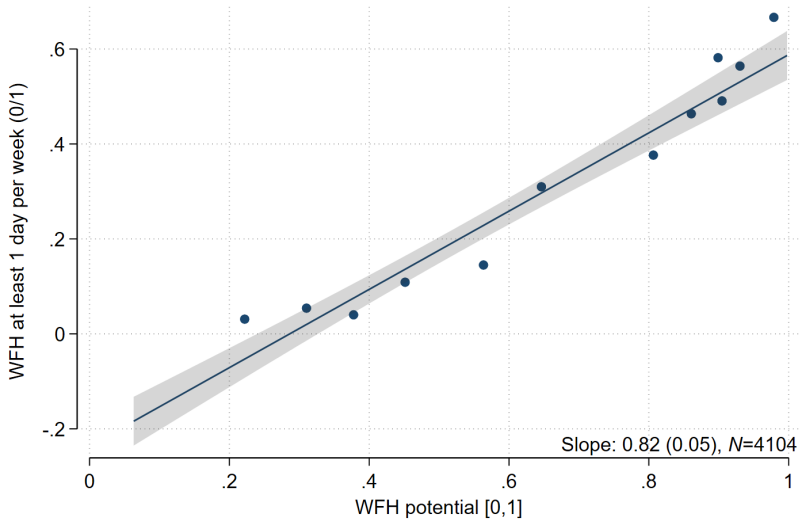
WFH potential and realized WFH. The insurance data do not report realized WFH. To validate our treatment, we show that greater exposure to the WFH shock strongly predicts realized WFH using individual-level data from the German Socioeconomic Panel (SOEP, Version 40.1). Figure 4 plots WFH at least one day per week in 2023 (0/1) against 2019 WFH potential for a sample of 4,165 employees aged 25–55 in 2019.[13] The slope estimate confirms that feasibility constraints have bite: moving WFH potential from zero to one increases the likelihood of working remotely in 2023 by 82 p.p., on average.

3 Empirical Strategy

We compare trends in the incidence of sick leave across individuals with different exposure to the WFH shock using a DiD framework. Our treatment variable is an individual i's WFH potential $WFH_{s(i)} \in [0,1]$, measured at the 3-digit occupation level s in February 2020. Given

[13] Average WFH potential in the SOEP sample is 0.596, consistent with the BARMER sample (0.58) and the BIBB-BAuA sample (0.59).

Figure 4: Effect of WFH potential on realized WFH (0/1) in 2023 (SOEP data)



Notes: The figure shows a binned scatter plot of WFH status in 2023 against 2019 WFH potential [0,1]. WFH status is a dummy for working remotely at least one day per week in 2023. Individual-level observations are grouped into equal-sized bins. The sample includes individuals employed and aged 26–55 in 2019. The 95% confidence band is calculated using standard errors clustered by 3-digit occupation. Data are from the Socioeconomic Panel (SOEP, Version 40.1).

that realized WFH is unobserved in the insurance data, the DiD estimates deliver "intention-to-treat" (ITT) effects of WFH. The dynamic DiD specification is given by:

$$y_{it} = \sum_{k \neq 2019m12} [\beta^k \mathbb{1}(t = k) \times WFH_{s(i)}] + \gamma_i + \gamma_t + \epsilon_{it}. \tag{1}$$

In the baseline, the outcome y_{it} is a dummy equal to one if individual i registers at least one day of sickness absence during year-month t, irrespective of the episode's onset. γ_i and γ_t correspond to individual and time-period fixed effects. The error term ϵ_{it} captures unobserved shocks, which are assumed to be uncorrelated with the treatment-period interactions. Then, the DiD coefficients β^k trace differences in monthly sick-leave probability associated with moving WFH potential from zero to one over time, relative to December 2019 (the reference period). We cluster standard errors by occupation, which corresponds to the level of treatment "assignment" (Abadie *et al.*, 2023).

Identifying assumption. As our setting involves a continuous treatment variable, the validity of the DiD design hinges on the *strong* parallel trends (SPT) assumption (Callaway *et al.*, 2024). Concretely, we require that the average trend observed for occupations at a given WFH potential matches the trend that would have been observed for all occupations if they had been assigned the same WFH potential. SPT ensures that lower-WFH-potential occupations serve as valid counterfactuals for higher-WFH-potential occupations, and vice versa. This assumption holds, for instance, if we rule out that individuals select into levels of WFH potential based on expected treatment effects. Because the Covid-induced shift to WFH was unexpected, it is

plausible that workers did not choose occupations in anticipation of future WFH opportunities. Moreover, the scale, access, and perception of WFH by both firms and workers changed fundamentally after 2020, so that even those with previous WFH experience were effectively "treated" by the WFH shock (Barrero *et al.*, 2023).

Validity. Like standard parallel trends, this assumption cannot be tested directly. We thus perform several checks to support internal validity. First, our event study design allows for a visual verification of parallel pre-trends. Nevertheless, they do not necessarily guarantee parallel development of potential outcomes in the post-treatment period. Thus, we also provide treatment effect estimates that take potential violations of the parallel trend assumption into account using the approach by Rambachan and Roth (2023). Second, we show robustness to including time fixed effects interacted with state, gender, age group, education, industry, and 1-digit occupation fixed effects, respectively. This restricts the identifying variation to within-group comparisons, addressing concerns about differential time trends that might stem from heterogeneous exposure to the pandemic.

Seasonality in sick leave. Because occupations with greater in-person interactions–and typically lower WFH potential–experience higher rates of sick leave during the flu seasons, a natural seasonality arises in the absenteeism differential across WFH potential even before the WFH shock. To account for such seasonal patterns, we apply a de-seasoning procedure before estimating our main DiD regressions. Specifically, we first estimate month-specific fixed effects for each occupation using the pre-treatment period (2018–2019) and subtract them from the entire occupation-specific time series before the DiD estimation. Then, our DiD estimates identify the ITT effect of WFH on sick leave beyond the usual seasonal differences expected in the absence of the big shift to remote work. Nevertheless, in Section 4.1, we also report the results using the original outcomes (i.e., without de-seasoning).

Spillovers. The nature of contagious diseases implies that a rise in WFH may also reduce infection risk for non-remote workers, whether at work, during their commute, or via family members. In other words, the infection-reducing effects of WFH likely spill over to occupations with low WFH potential. Because the DiD estimates capture only the differential effect between high- and low-WFH-potential occupations, we may therefore underestimate the *direct* effect of WFH on individuals in remote occupations. This is particularly true when absenteeism is driven primarily by actual illness rather than by behavioral factors. We provide evidence on this issue in Section 5.

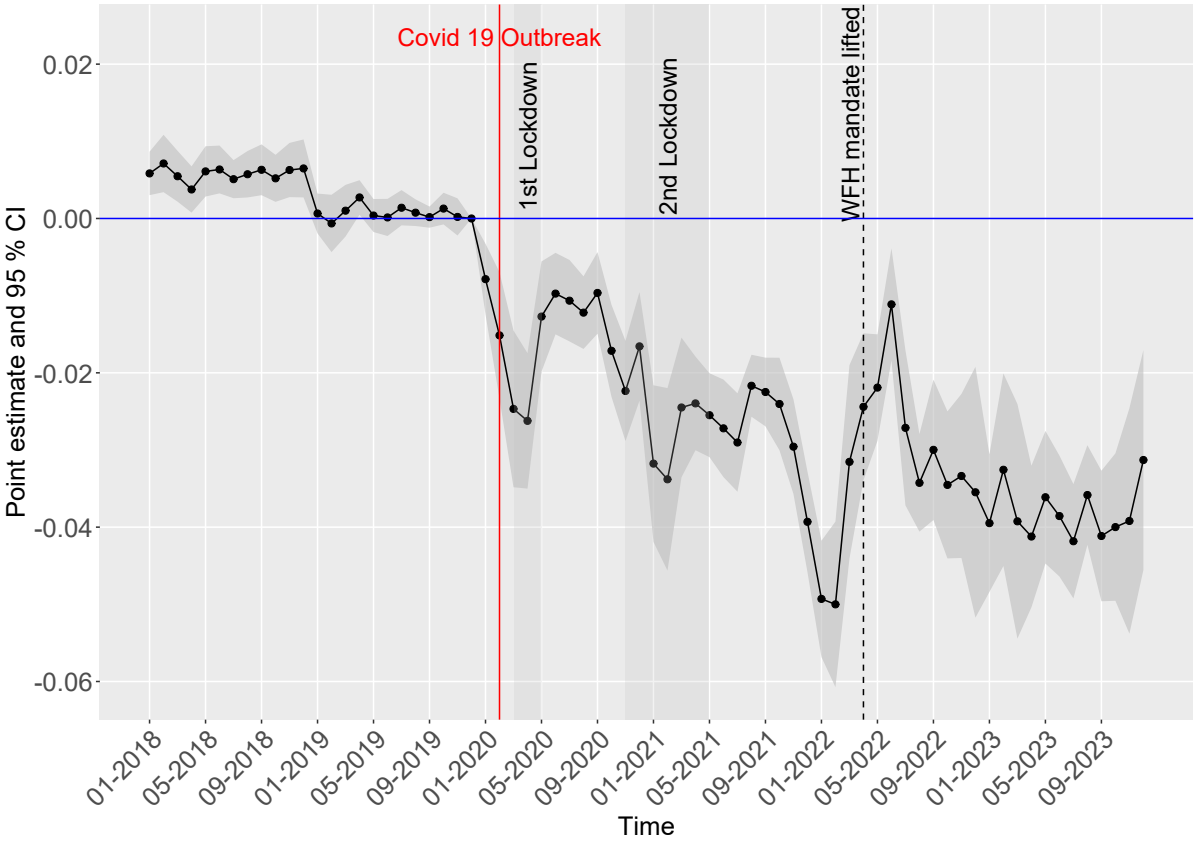
4 Results

4.1 Main Results

We begin by providing graphical evidence of the intention-to-treat effects of WFH potential on the probability of sick leave over time. The outcome is a dummy equal to one if the worker

registers one or more sick-leave days during the month, independent of the spell's start date. Figure 5 plots the event-study estimates from the interaction of WFH potential with month dummies along with 95% confidence intervals (Equation 1). The reference period is December 2019. The outcome variable is de-seasonalized, i.e., net of occupation-specific month fixed effects, estimated using the pre-treatment years (2018 and 2019). The event study using the unadjusted outcome is slightly noisier but delivers similar conclusions (see Appendix Figure C.5).

Figure 5: Event-study estimates of WFH Potential on Monthly Sick Leave (0/1)



Notes: The figure presents event study based on Equation 1. The outcome is an indicator equal to one if an individual is absent one or more days in a given calendar month. The sample is a balanced panel of employed individuals aged 26–55 as of February 15, 2020, observed monthly from 01/2018 to 12/2023. 95% confidence intervals are calculated using standard errors clustered by 3-digit occupation.

The estimates show no systematic association between WFH potential and the monthly likelihood of sick leave before 2020. Coefficients are close to zero; albeit statistically significant in 2018, which is not surprising given the large sample. Nonetheless, we address concerns about violations of parallel trends by presenting bounds on treatment effects following the approach of Rambachan and Roth (2023).

At the onset of the pandemic, absenteeism incidence sharply diverges across individuals with different WFH potential: higher exposure to the WFH shock significantly reduces the likelihood of registering at least one day of absence within the month. The effect spikes during

lockdowns and the winter of 2022/23, coinciding with Covid-19 infection waves. Remarkably, the effect remains significant and stabilizes after the end of the public health emergency (Summer 2022). The point estimates imply that by 2023, an increase in the WFH potential by 10 p.p. reduces the probability of sick leave within the month by about 0.4 p.p. This corresponds to a 3.3% decline relative to the pre-treatment sick leave rate, indicating a nontrivial persistent response to WFH. For reference, a 10 p.p. difference in WFH potential corresponds, for instance, to the gap between jobs in performing and entertainment professions and media documentation and information services.

A reasonable explanation for why the post-pandemic absenteeism effect exceeds that during the pandemic is the extensive use of short-time work (STW), which allowed companies to reduce labor costs by cutting working hours during the crisis.[14] In the first lockdown alone, STW affected about 6 million (18% of) employees, primarily in non-teleworkable occupations and industries subject to mandatory closures (Alipour *et al.*, 2021; Adams-Prassl *et al.*, 2020; Ben Yahmed *et al.*, 2024). Given that STW reduces employees' workplace exposure to Covid-19, the infection-shielding effect of WFH captured by DiD estimates appears heavily muted until the end of the pandemic.

Table 1 presents the DiD point estimates from our baseline specification (column 1) and extensions, which restrict the identifying variation to regional, demographic, educational, industrial, and worker subgroups. For expositional clarity, we present annual average effects by interacting the WFH index with year dummies (relative to 2018 and 2019), while retaining month-year fixed effects.[15] Column 1 confirms that an increase in WFH potential by 10 p.p. reduces monthly sick leave probability by 0.4 p.p. in 2023, or 3.3% relative to the pre-pandemic mean. Columns 2–6 demonstrate that the point estimates are insensitive to allowing the time fixed effects to vary by state, gender, age-group, education, (1-digit) industry, respectively. This reassures us that neither individual heterogeneity nor differential regional, demographic, or industry shocks confounds the estimated effects of WFH exposure on absenteeism. Column 7 adds interactions between event-time and 1-digit occupations to our main specification. This is a very conservative approach because these interactions already partly absorb treatment effects attributable to differences in WFH potential across broader occupational groups. Although the point estimates decrease by about one-third, identifying the effects from within-occupation variation in WFH potential alone still yields a significant and persistent reduction in sick leave. Column 8 confirms these conclusions by incorporating all group-specific time fixed effects simultaneously.

[14] The STW scheme (*Kurzarbeit*) is designed to prevent layoffs while allowing companies to reduce labor costs during economic crises. Wage losses are partly compensated through the unemployment insurance. The German STW scheme was expanded during the Covid crisis, such that unemployment barely increased (Ben Yahmed *et al.*, 2024).

[15] Specifically, we report the DiD estimates β^g from specification:
$y_{it} = \sum_{g \neq 2019} [\beta^g \mathbb{1}(g = \text{year}(t)) \times WFH_{s(i)}] + \gamma_i + \gamma_t + \epsilon_{it}$.

Table 1: Year-Specific Effects of WFH Potential on the Probability of Sick Leave (0/1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WFH potential								
× Dummy 2020	-0.01865***	-0.01881***	-0.02019***	-0.01814***	-0.01870***	-0.01568***	-0.01596***	-0.01117***
	(0.00252)	(0.00254)	(0.00224)	(0.00249)	(0.00248)	(0.00196)	(0.00312)	(0.00264)
× Dummy 2021	-0.03098***	-0.03071***	-0.03189***	-0.03035***	-0.03039***	-0.02833***	-0.02321***	-0.01863***
	(0.00252)	(0.00253)	(0.00244)	(0.00255)	(0.00258)	(0.00210)	(0.00341)	(0.00280)
× Dummy 2022	-0.03516***	-0.03483***	-0.03753***	-0.03517***	-0.03365***	-0.03644***	-0.02347***	-0.02205***
	(0.00441)	(0.00435)	(0.00396)	(0.00439)	(0.00447)	(0.00291)	(0.00744)	(0.00494)
× Dummy 2023	-0.04128***	-0.04212***	-0.04173***	-0.04238***	-0.03831***	-0.04122***	-0.02560***	-0.02408***
	(0.00498)	(0.00493)	(0.00469)	(0.00469)	(0.00526)	(0.00372)	(0.00754)	(0.00490)
Mean dep. var.	0.12454	0.12454	0.12454	0.12454	0.12454	0.12454	0.12454	0.12454
Individuals	1,867,637	1,863,178	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,863,178
Time FE	✓							
State × Time FE		✓						✓
Gender × Time FE			✓					✓
Age Group × Time FE				✓				✓
Education × Time FE					✓			✓
Industry × Time FE						✓		✓
Occupation × Time FE							✓	✓

Notes: The table presents DiD estimates based on a version of Equation 1, in which WFH×month-year interactions are replaced by WFH×year interactions. The reference year is 2019. The outcome is a dummy equal to one if the worker registers one or more sick-leave days during the month, independent of the spell's start date. The sample is a balanced panel of employed individuals aged 26–55 as of February 15, 2020, observed monthly from 01/2018 to 12/2023. Mean dependent variable is calculated over the 2018–2019 pre-treatment period. Categorical variables include fixed effects for 16 states, six age groups (26–30, 31–35, 36–40, 41–45, 46–50, 51–55), seven education levels (unknown, without professional qualification, completed apprenticeship, Master craftsperson, Bachelor's degree, Master's degree, PhD), XX industries, and nine 1-digit occupational groups. Standard errors are clustered by 3-digit occupation and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

4.2 Results by Diagnosis

Table 2 examines the different health causes of sickness absence. For this purpose, we run regressions similar to those in Section 4.1, but replace the dependent variable with indicators for sick leave due to a specific ICD-10 code. We focus on the most frequent ICD-10 groups (see Figure 2). In addition, we consider codes for special purposes (group *U*), as they include the ICD-10 codes *U7.1* and *U7.2* used for Covid-19 diagnosis. The remaining diagnoses are combined in the category *Other*.[16] Given the large number of outcomes, Table B.3 in the Appendix shows that the conclusions hold when we account for multiple hypothesis testing.

Table 2 reproduces the baseline estimates in column 1 and subsequently breaks down the overall effect by ICD-10 groups. Higher WFH exposure significantly reduces sick leave across all categories, but effects for Covid-19 (group U) are small and short-lived. In contrast, effects for other diagnosis groups persist through 2023 and typically grow over time.

In the post-Covid economy (2023), the overall effect of WFH exposure (column 1) is driven mainly by reductions in leaves due to musculoskeletal disorders (group *M*), which account for just over 40% of the total decline in sickness absence. Reductions in respiratory diseases (group *J*), the most frequent diagnosis group, explain about 20% of the overall effect, followed by infectious and parasitic diseases (group *A&B*) at roughly 13%. Reduced absenteeism due to mental and behavioral disorders (group *F*), diseases of the digestive system (group *K*), and nonspecific symptoms (group *R*) each accounts for roughly 7% of the overall effect. Injuries and poisoning (groups *S&T*) play a minor role, accounting for less than 4%, while the remaining diagnoses together explain about 15% of the overall effect.

Relative to pre-treatment means, a 10 p.p. increase in WFH potential reduces sick leave due to musculoskeletal disorders by 7.9%, which is more than twice the average effect across all diagnoses (3.3%). Reductions for respiratory diseases and nonspecific symptoms are also sizable (about 4.6%), while effects for the remaining diagnoses are smaller than for the average sick leave effect of WFH exposure.

The large impact of WFH on sick leave due to musculoskeletal disorders (group *M*) is noteworthy for two reasons. First, WFH may allow employees to break up sedentary work with home activities and more flexible movement patterns, potentially alleviating musculoskeletal strain from prolonged sitting (Putsa *et al.*, 2022). Second, this ICD-10 group includes relatively subjective symptoms such as back pain, which are a frequent cause of medically certified absence but are difficult for a physician to verify objectively under asymmetric information (Carlsen *et al.*, 2020). To the extent that WFH improves working conditions and job satisfaction, it may reduce incentives for strategic sick-leave take-up for such hard-to-verify symptoms. These mechanisms operate in the same direction and cannot be disentangled in our setting.

[16] Physicians can list multiple diagnoses on the same sick leave certificate. Therefore, the sum of the means across columns 2 through 10 (of 0.131) is slightly higher than the total mean incidence of sick leave in column 1.

Table 2: Effects on the Probability of Sick Leave by Diagnosis

	(1) All	(2) J Respiratory	(3) M Muscular	(4) F Mental	(5) S & T Injuries	(6) A & B Infections	(7) K Digestive	(8) R Symptoms	(9) U Covid	(10) Other
WFH potential										
× Dummy 2020	-0.01865***	-0.00563***	-0.00682***	-0.00105**	-0.00032	-0.00140***	-0.00061***	-0.00087***	-0.00037*	-0.00262***
	(0.00252)	(0.00098)	(0.00068)	(0.00050)	(0.00032)	(0.00033)	(0.00023)	(0.00019)	(0.00022)	(0.00039)
× Dummy 2021	-0.03098***	-0.00809***	-0.00996***	-0.00164**	-0.00242***	-0.00197***	-0.00080***	-0.00230***	-0.00175***	-0.00425***
	(0.00252)	(0.00122)	(0.00084)	(0.00080)	(0.00045)	(0.00033)	(0.00025)	(0.00030)	(0.00028)	(0.00044)
× Dummy 2022	-0.03516***	-0.00721***	-0.01305***	-0.00292***	-0.00167***	-0.00410***	-0.00189***	-0.00289***	-0.00015	-0.00586***
	(0.00441)	(0.00243)	(0.00091)	(0.00096)	(0.00034)	(0.00046)	(0.00019)	(0.00037)	(0.00118)	(0.00050)
× Dummy 2023	-0.04128***	-0.00790***	-0.01676***	-0.00286***	-0.00161***	-0.00548***	-0.00285***	-0.00306***	0.00041	-0.00629***
	(0.00498)	(0.00271)	(0.00128)	(0.00091)	(0.00035)	(0.00065)	(0.00034)	(0.00045)	(0.00110)	(0.00059)
Mean dep. var.	0.12454	0.03433	0.02119	0.01263	0.01201	0.01172	0.01062	0.00667	4.16×10^{-5}	0.02160
Individuals	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The outcome is a dummy equal to one if the worker registers one ore more sick leave days due to a certain ICD-10 diagnosis during the month, independent of the spell's start date. The sample is a balanced panel of employed individuals aged 26–55 as of February 15, 2020, observed monthly from 01/2018 to 12/2023. Mean dependent variable is calculated over the 2018–2019 pre-treatment period. Standard errors are clustered by 3-digit occupation and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Overall, Table 2 suggests that a higher WFH potential reduces sickness absence, with the largest contribution coming from musculoskeletal conditions. We also find meaningful reductions in sick leave due to respiratory diseases and infectious and parasitic diseases (i.e., diagnoses commonly associated with sore throats, colds, influenza, and gastrointestinal infections). This pattern is consistent with a reduced risk of workplace transmission when work is performed remotely.

4.3 Effects on Sick Leave Duration

We next examine the effect of WFH exposure on sick leave duration in Table 3. Column 1 reproduces the baseline result (for the extensive margin). Column 2 reports estimates on the total number of sick days per month, which captures both extensive and intensive margin responses: the point estimates suggest 0.056 fewer days per month (a 4.5% reduction) for a 10 p.p. increase in WFH potential in 2023. This effect is equivalent to nearly seven additional days per year associated with an increase in WFH potential from 0 to 1.

Columns 3–7 decompose the effects by thresholds of monthly sick-leave duration.[17] Given their higher frequency, short-duration absences account for a larger share of the overall effect. However, relative to their low pre-treatment means, the estimates for long- and medium-duration absences imply large percentage reductions. In 2023, a 10 p.p. increase in WFH potential reduces the probability of having more than one sick day per month by 3.3%, more than three days by 3.6%, and more than five days by 4.2% (all relative to the corresponding pre-treatment mean), while longer absences of more than twelve and more than 26 days show effect sizes of 4.9% and 6.9%, respectively. In absolute terms, the point estimates for absences longer than 12 and 26 days amount to roughly 40% and 27% of the overall reduction in the probability of any sick leave (in column 1), respectively. Because the duration thresholds in columns 3–7 are nested, these shares are not additive. Nevertheless, they indicate that a substantial portion of the extensive-margin response reflects declines in longer absences.

Overall, the results indicate that the main effect is not driven solely by reductions in very short durations: longer sick-leave absences also decline, and proportionally by at least as much.

5 Potential Mechanisms

5.1 Health vs. Behavioral Responses

Our key finding is that WFH exposure reduces sick leave in the long run, primarily through lower absences due to musculoskeletal disorders and respiratory diseases. The persistence of the effects, together with the fact that longer absence spells decrease by at least as much as very

[17] We choose these thresholds based on the distribution of monthly absence durations (see Appendix Figure C.3): conditional on taking sick leave, more than half of employees are absent for less than one workweek per month, with mass points at three and five days. There is an additional mass point at 12 days, corresponding to two workweeks. Months with longer absences are comparatively rare.

Table 3: Effects of WFH Potential on Sick Leave Duration

	(1) ≥ 1 day (baseline)	(2) No. of days	(3) > 1 day	(4) > 3 days	(5) > 5 days	(6) > 12 days	(7) > 26 days
WFH potential							
× Dummy 2020	-0.01865***	-0.29276***	-0.01654***	-0.01291***	-0.01119***	-0.00919***	-0.00721***
	(0.00252)	(0.03210)	(0.00229)	(0.00187)	(0.00149)	(0.00103)	(0.00069)
× Dummy 2021	-0.03098***	-0.42722***	-0.02785***	-0.02075***	-0.01628***	-0.01283***	-0.00997***
	(0.00252)	(0.04224)	(0.00241)	(0.00202)	(0.00172)	(0.00142)	(0.00108)
× Dummy 2022	-0.03516***	-0.51648***	-0.03182***	-0.02553***	-0.02358***	-0.01649***	-0.01090***
	(0.00441)	(0.06168)	(0.00419)	(0.00376)	(0.00339)	(0.00214)	(0.00123)
× Dummy 2023	-0.04128***	-0.55871***	-0.03732***	-0.03159***	-0.02697***	-0.01642***	-0.01123***
	(0.00498)	(0.05262)	(0.00469)	(0.00390)	(0.00310)	(0.00146)	(0.00094)
Mean dep. var.	0.12454	1.24410	0.11320	0.08731	0.06379	0.03339	0.01629
Individuals	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637
Time FE	✓	✓	✓	✓	✓	✓	✓

Notes: The table presents DiD estimates based on a version of Equation 1, in which WFH×month-year interactions are replaced by WFH×year interactions. The reference year is 2019. Except for column 2, the outcome is a dummy equal to one if the worker registers the indicated number of sick days during the month, independent of the spell's start date. In column 2, the outcome is the absolute number of sick days during the month, independent of the spell's start date. The sample is a balanced panel of employed individuals aged 26–55 as of February 15, 2020, observed monthly from 01/2018 to 12/2023. Mean dependent variable is calculated over the 2018–2019 pre-treatment period. Standard errors are clustered by 3-digit occupation and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

short spells, suggests that our results are unlikely to be driven solely by behavioral responses. For example, if higher WFH potential mainly increased presenteeism, we might indeed expect a short-run reduction in sick-leave usage. However, if sustained presenteeism has negative health consequences later on (e.g., Hansen and Andersen, 2009; Patel *et al.*, 2023), sick leave should increase in the long run, at both the extensive and intensive margins. Our estimates imply the opposite pattern. Nevertheless, to shed more light on this issue, we examine outcomes that are less directly tied to sick-leave certification, namely all doctor visits (independent of an AU certificate) and hospital stays.

Table 4 reports the results. For comparison, column 1 repeats our main results for the effect on sick leave take-up in a given month. Note that in column 2, the mean probability of any doctor visit in a given month is 43%, i.e., substantially higher than sick leave itself (mean of 12%). This is unsurprising, since some visits reflect routine check-ups, prescription renewals, or preventive care rather than acute illness. In general, we find significant reductions in the probability of a doctor visit, but the point estimates are smaller in magnitude compared to the effects on sick leave column 1. Specifically, in 2023, a 10 p.p. increase in WFH potential reduces the probability of any doctor visit by about 0.25 p.p., which corresponds to roughly a 0.6% decline relative to the mean. One interpretation is that WFH may facilitate some visits during working hours (e.g., routine appointments), which would work against a decline in utilization. Given that our estimates capture the net effect, the negative point estimates are consistent with genuine health improvements.

To assess which conditions drive the decline in utilization, we further break down doctor visits by ICD-10 group (Appendix Table B.4).[18] We find statistically significant reductions across all diagnosis groups throughout. Interestingly, in 2023, the largest relative reduction occurs for group *U* (special purposes, including COVID-related codes), where a 10 p.p. increase in WFH potential lowers the probability of a visit by about 0.40 p.p. (roughly 3.4% relative to the mean). Since we only found temporary effects on sick-leave take-up for this group (see Table 2), the persistent and substantial effects on doctor visits suggest that WFH has a protective effect on symptoms related to the virus, including "long Covid". Nevertheless, we also find substantially lower probability of visits due to musculoskeletal problems (group M) of 1.6%, while visits due to respiratory diseases (group *J*), mental and behavioral disorders (group *F*), and abnormal symptoms (group *R*) decline by roughly 1.1–1.5% relative to their respective means.

Finally, column 3 of Table 4 shows that the probability of a hospital stays also declines with WFH exposure. While hospitalizations are rare (mean 1.3% per month), the 2023 estimate implies that a 10 p.p. increase in WFH potential reduces the probability of a hospital stay by roughly 1.3% relative to the mean. Disaggregating by diagnosis groups (see Appendix

[18] The sum of group-specific means for the diagnosis indicators exceeds one (about 1.15) because a single visit can generate multiple diagnoses.

Table B.5) suggests that these reductions are concentrated in hospital stays related to musculoskeletal disorders (group *M*) and mental and behavioral disorders (group *F*), which are also the most common reasons for hospitalization. We do not detect meaningful changes for other ICD-10 groups). Overall, this evidence is consistent with WFH exposure leading to improved health rather than merely shifting the propensity to file an AU certificate. This conclusion also applies along clinically more severe margins.

Table 4: Effects on the Probability of any Doctor Visit and Hospital Stay

	(1)	(2)	(3)
	Main (Sick Leave)	Doctor Visit	Hospital Stay
WFH potential			
× Dummy 2020	-0.01865***	-0.01523***	-0.00023
	(0.00252)	(0.00328)	(0.00018)
× Dummy 2021	-0.03098***	-0.02010***	-0.00047***
	(0.00252)	(0.00216)	(0.00018)
× Dummy 2022	-0.03516***	-0.03037***	-0.00116***
	(0.00441)	(0.00292)	(0.00022)
× Dummy 2023	-0.04128***	-0.02464***	-0.00179***
	(0.00498)	(0.00276)	(0.00033)
Mean dep. var.	0.12454	0.43409	0.01326
Observations	134,469,864	134,469,864	134,767,512
R^2	0.14543	0.22272	0.04669
Within R^2	0.00017	4.65×10^{-5}	2.31×10^{-6}
Time FE	✓	✓	✓
ID FE	1,867,637	1,867,637	1,871,771

Notes: Regressions do not include control variables. Standard errors are clustered at 3-digit occupation level and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

5.2 Heterogeneity by Gender and Age

Our baseline estimates indicate that greater exposure to the WFH shock reduces absenteeism on average; but these effects may mask meaningful heterogeneity across demographic groups. Age and gender are two dimensions along which both exposure to illness and the incentives to substitute WFH for formal sick leave differ systematically. First, older workers face a higher prevalence of chronic and serious health conditions that limit their ability to work while sick, even remotely. Younger workers, by contrast, more often experience short, mild illnesses for which WFH could facilitate presenteeism. They may also face stronger career incentives to remain available. We therefore expect WFH to have a larger impact on sick leave among younger employees. Second, women exhibit higher baseline sickness absence and shoulder a disproportionate share of caregiving responsibilities (Bredtmann, 2014). WFH may allow employees to keep working while managing minor illnesses or care responsibilities, reducing the need for formal sick leave (Gibbs *et al.*, 2023; Laß *et al.*, 2025; Ichino and Moretti, 2009). We expect this channel to be strongest for women at the typical ages when they typically face dual care responsibilities.

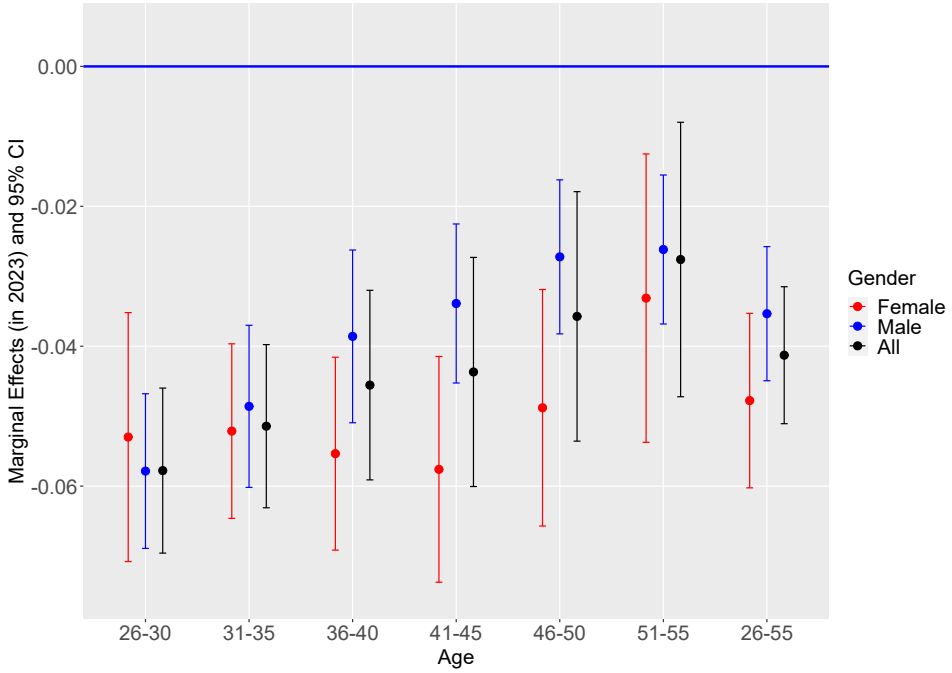
We explore heterogeneous effects of WFH potential across gender and six age groups, defined in five-year intervals, using a fully interacted version of model Equation 1. This yields DiD estimates of the impact of WFH potential on sick leave probability for each gender-age subgroup in each post-treatment year. Figure 6 plots the marginal effects of WFH potential for each subgroup in 2023.[19] The last set of estimates on the right (age 26–55) shows the average gender-specific effects, regardless of specific age. To interpret the results, it is important to establish whether WFH opportunities are realized at similar rates across these groups. Using auxiliary SOEP data, we find that the "first-stage" effect of WFH potential on the probability of actually working remotely at least one day per week in 2023 is remarkably similar across gender-age groups (see Appendix Figure C.19).[20] This suggests that any heterogeneity in absenteeism responses to WFH potential should not primarily reflect differences in WFH uptake.

Figure 6 reveals a clear age gradient: the absenteeism-reducing effect of WFH declines with age, particularly, among men. For women, the gradient is flatter up to age 45, but similarly attenuates thereafter. Overall, women tend to respond more strongly to WFH potential than men of comparable ages. We find the strongest reduction in sick leave among women aged 41–45, followed by those aged 36–40, consistent with our prior expectations. In sum, the evidence suggests that women and younger workers benefit most from access to WFH.

[19] For completeness, Appendix Figure C.12 through Figure C.14 show the results for 2020 through 2022.

[20] While the point estimates suggest a slightly lower uptake among women in the youngest age group (26—30 and 31—35), these differences are not statistically significant. Thus, if anything, the reduced-form effects for women up to age 35 in Figure 6 correspond to somewhat stronger absenteeism responses than those for men.

Figure 6: Effect of WFH Potential on Monthly Sick Leave Probability by Age and Gender, 2023



Notes:

6 Conclusion

We study the impact of work-from-home opportunities on sick leave at the workplace using individual-level data from a large German health insurance covering 2018-2023. Difference-in-difference estimations show that sickness absence decreases among those individuals who work in occupations with a high WFH potential. The effect comes mainly from milder diseases such as infection and back pain. Our analysis of doctor visits independent of sick leaves and data on hospitalizations suggests that the effect is driven by both health effects and behavioral changes. We also find significant heterogeneity across gender and age. Women respond stronger to work-from-home opportunities than men, whereas the gender difference is most pronounced in those age groups where women have frequent childcare obligations.

Our results point to some policy-relevant effects of WFH. In Germany, we observe a trend in increasing sick leave days and uptake of WFH. However, our causal estimations suggest that WFH is not responsible for this trend; quite the opposite is happening.

Our unique health insurance data does not allow us to match individuals to firms or industries, which would provide us with more information about the specific work, or to match spouses or families. Therefore, we cannot identify the exact mechanisms behind our results. It is somewhat speculative but plausible to interpret our results in a way that women gain from WFH since they can better organize work and family duties. WFH adds flexibility, which seems most important for women of a certain age. Also, younger people respond relatively strong to WFH, which might be caused by the higher adaptability of young people to changes

in the work environment and the use of modern telecommunication infrastructure. Finally, we find people in urban areas to react more sensitive, which might be caused by better internet infrastructure, larger firms, or different work-ethics.

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Appendix A Labor market policies

Stay-at-home order and WFH mandate. While initial pandemic restrictions in late February 2020 were largely local, a nationwide lockdown, including a stay-at-home order and a ban on gatherings of more than two people, was implemented on March 22 and remained in effect until May 6, 2020. During this period, entire sectors were ordered to close, and the government strongly recommended that employers implement WFH where feasible. By December 2020, stricter measures were deemed necessary, leading to renewed hard lockdowns that persisted through spring 2021. In January 2021, the government implemented a legal WFH mandate under the Infection Protection Act (*Infektionsschutzgesetz*), obliging employers to enable WFH unless compelling operational reasons prevented it. In addition, the government introduced a tax-incentive for remote work (*Homeoffice-Pauschale*) that was made permanent in 2023.[21]

Short-time work (STW). To avert mass layoffs, the federal government expanded access to short-time work (*Kurzarbeit*). Nearly one-third of the workforce participated in the scheme at the height of the crisis (Fitzenberger and Walwei, 2023).[22] Meanwhile, remote work emerged as a strategy to mitigate infection risk while maintaining operations alive. Evidence shows that WFH shielded workers from STW and job loss during the pandemic (Alipour *et al.*, 2021; Adams-Prassl *et al.*, 2020).

[21] Since 2023, employees in Germany can claim up to 210 days of remote work in their income tax declaration at a rate of €6 per day, amounting to a maximum of €1,260 per year.

[22] *Kurzarbeit* compensates employees for earnings losses due to reduced working hours by reimbursing firms severely affected by the pandemic for up to two-thirds of foregone wages.

Appendix B Tables

Table B.1: Descriptive Statistics

	Mean	SD
Main Characteristics		
Female	57.09	
Age	41.69	8.79
Age group: 26 - 30	0.136	
Age group: 31 - 35	0.158	
Age group: 36 - 40	0.163	
Age group: 41 - 45	0.151	
Age group: 46 - 50	0.167	
Age group: 51 - 55	0.224	
Occupation: Agriculture, forestry, animal husbandry and landscaping	0.011	
Occupation: Extraction of raw materials, production and manufacturing	0.167	
Occupation: Construction and architecture	0.041	
Occupation: Natural sciences, geography and information technology	0.032	
Occupation: Transportation, logistics, protection and security	0.11	
Occupation: Commercial services, trade in goods, tourism, hospitality	0.128	
Occupation: Business organization, accounting, law and administration	0.232	
Occupation: Health, social work, teaching, education	0.247	
Occupation: Literature, social and economic sciences, media, culture	0.032	
Outcomes		
At least one day of sick-leave day during the month (0/1) 2018	0.122	0.328
At least one day of sick-leave day during the month (0/1) 2019	0.126	0.332
At least one day of sick-leave day during the month (0/1) 2020	0.122	0.327
At least one day of sick-leave day during the month (0/1) 2021	0.123	0.328
At least one day of sick-leave day during the month (0/1) 2022	0.185	0.389
At least one day of sick-leave day during the month (0/1) 2023	0.191	0.393
Number of absent days per month 2018	1.211	4.617
Number of absent days per month 2019	1.283	4.821
Number of absent days per month 2020	1.446	5.304
Number of absent days per month 2021	1.496	5.491
Number of absent days per month 2022	1.956	5.824
Number of absent days per month 2023	1.929	5.810
Treatment		
Work from home (WFH) feasibility	0.58	0.26

Notes: Sample restricted to individuals employed on February 15, 2020 and aged 26–55. Main characteristics and WFH feasibility measured as of this cutoff day.

Table B.2: Insurance Sample versus Population Benchmark

	Insurance sample		SOEP	
	(1)	(2)	(3)	(4)
	Mean	SD	Mean	SD
Demographics				
Age	41.69	8.79	42.482	8.277
Age group: 26-30	0.136		0.109	
Age group: 31-35	0.158		0.126	
Age group: 36-40	0.163		0.161	
Age group: 41-45	0.151		0.185	
Age group: 46-50	0.167		0.208	
Age group: 51-55	0.224		0.211	
Female	57.09		0.508	
Occupation: Agriculture, forestry, animal husbandry and landscaping	0.011		0.013	
Occupation: Business organization, accounting, law and administration	0.232		0.219	
Occupation: Commercial services, trade in goods, tourism, hospitality	0.128		0.104	
Occupation: Construction and architecture	0.041		0.046	
Occupation: Extraction of raw materials, production and manufacturing	0.167		0.171	
Occupation: Health, social work, teaching, education	0.247		0.230	
Occupation: Literature, social and economic sciences, media, culture	0.032		0.029	
Occupation: Natural sciences, geography and information technology	0.032		0.045	
Occupation: Transportation, logistics, protection and security	0.110		0.142	
Working from home				
WFH at least 1 day/ week, 2023			0.301	
WFH potential (3-digit occupation)	0.580	0.260	0.596	0.271

Notes: The table reports summary statistics for employees in the insurance data (as of February 2020) and, for comparison, a representative sample of employees in 2019 from the Socioeconomic Panel (SOEP, Version 40.1). Both samples are restricted to employees aged 26–55.

Table B.3: Effect of WFH Potential on Sickness Leave by Diagnosis with Aggregated Data and Multiple Hypothesis Testing (Romano Wolf)

	(1) All	(2) J	(3) M	(4) A & B	(5) K	(6) S & T	(7) F	(8) R	(9) U	(10) Other
Dummy_2020	-0.01009***	-0.00415***	-0.00276***	-0.00104***	-0.00037*	0.00036	-0.00049**	-0.00059***	-0.00023	-0.00154***
	(0.00187)	(0.00082)	(0.00037)	(0.00029)	(0.00021)	(0.00024)	(0.00023)	(0.00015)	(0.00017)	(0.00023)
	[0.00040]	[0.00070]	[0.00010]	[0.01090]	[0.27310]	[0.31390]	[0.18150]	[0.00680]	[0.31390]	[0.00010]
Dummy_2021	-0.01955***	-0.00696***	-0.00435***	-0.00166***	-0.00056**	-0.00133***	-0.00087***	-0.00180***	-0.00131***	-0.00243***
	(0.00196)	(0.00121)	(0.00038)	(0.00035)	(0.00026)	(0.00031)	(0.00030)	(0.00020)	(0.00020)	(0.00030)
	[0.00010]	[0.00010]	[0.00010]	[0.00060]	[0.04590]	[0.00140]	[0.02340]	[0.00010]	[0.00010]	[0.00010]
Dummy_2022	-0.01790***	-0.00452**	-0.00569***	-0.00291***	-0.00125***	-0.00022	-0.00147***	-0.00198***	0.00037	-0.00314***
	(0.00363)	(0.00204)	(0.00053)	(0.00037)	(0.00028)	(0.00019)	(0.00031)	(0.00028)	(0.00081)	(0.00039)
	[0.00320]	[0.13400]	[0.00010]	[0.00010]	[0.00320]	[0.46080]	[0.00320]	[0.00010]	[0.66030]	[0.00010]
Dummy_2023	-0.01869***	-0.00450*	-0.00700***	-0.00360***	-0.00165***	0.00038	-0.00123***	-0.00211***	0.00065	-0.00280***
	(0.00464)	(0.00238)	(0.00081)	(0.00058)	(0.00040)	(0.00024)	(0.00037)	(0.00036)	(0.00077)	(0.00056)
	[0.00760]	[0.23910]	[0.00010]	[0.00020]	[0.00760]	[0.26820]	[0.02020]	[0.00020]	[0.43590]	[0.00140]
Mean dep. var.	0.10019	0.02998	0.01669	0.01011	0.01024	0.00789	0.00703	0.00585	3.53×10^{-5}	0.01719
Observations	182,249,784	182,249,784	182,249,784	182,249,784	182,249,784	182,249,784	182,249,784	182,249,784	182,249,784	182,249,784
R^2	0.09214	0.05492	0.04987	0.03590	0.03340	0.02401	0.03748	0.02774	0.02163	0.04527
Within R^2	5.36×10^{-5}	1.43×10^{-5}	2.91×10^{-5}	1.27×10^{-5}	2.85×10^{-6}	2.85×10^{-6}	2.8×10^{-6}	8.28×10^{-6}	8.62×10^{-6}	6.4×10^{-6}
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
ID fixed effects	2,531,247	2,531,247	2,531,247	2,531,247	2,531,247	2,531,247	2,531,247	2,531,247	2,531,247	2,531,247

Notes: Regressions do not include control variables. Standard errors are clustered at KldB_3 level. * p<0.10, ** p<0.05, *** p<0.01. In square brackets: Romano Wolf corrected p-values for multiple hypothesis testing.

Table B.4: Effects on the Probability of Doctor Visit by Diagnosis Group

	(1) All	(2) J	(3) M	(4) F	(5) S & T	(6) A & B	(7) K	(8) R	(9) U	(10) Other
WFH Probability										
× Dummy 2020	-0.01523***	-0.00964***	-0.01211***	-0.00568***	-0.00313***	-0.00420***	-0.00471***	-0.00733***	-0.04436***	-0.01195***
	(0.00328)	(0.00243)	(0.00157)	(0.00112)	(0.00064)	(0.00101)	(0.00064)	(0.00115)	(0.01189)	(0.00349)
× Dummy 2021	-0.02010***	-0.01469***	-0.01964***	-0.00915***	-0.00827***	-0.00530***	-0.00708***	-0.01252***	-0.04098***	-0.01818***
	(0.00216)	(0.00163)	(0.00155)	(0.00132)	(0.00080)	(0.00084)	(0.00078)	(0.00105)	(0.01472)	(0.00192)
× Dummy 2022	-0.03037***	-0.01441***	-0.02430***	-0.01362***	-0.00617***	-0.00795***	-0.00937***	-0.01425***	-0.04541***	-0.02678***
	(0.00292)	(0.00321)	(0.00189)	(0.00179)	(0.00067)	(0.00089)	(0.00089)	(0.00140)	(0.01105)	(0.00262)
× Dummy 2023	-0.02464***	-0.01463***	-0.02378***	-0.01503***	-0.00473***	-0.00679***	-0.00955***	-0.01492***	-0.03958***	-0.02301***
	(0.00276)	(0.00288)	(0.00225)	(0.00184)	(0.00096)	(0.00095)	(0.00124)	(0.00122)	(0.01043)	(0.00240)
Mean dep. var.	0.43409	0.12943	0.15160	0.12006	0.06056	0.05795	0.08027	0.09755	0.11672	0.33925
Observations	134,469,864	134,469,864	134,469,864	134,469,864	134,469,864	134,469,864	134,469,864	134,469,864	134,469,864	134,469,864
R^2	0.22272	0.20995	0.26999	0.35526	0.20723	0.12715	0.29767	0.19792	0.08846	0.23889
Within R^2	4.65×10^{-5}	3.01×10^{-5}	6.91×10^{-5}	3.18×10^{-5}	1.29×10^{-5}	1.33×10^{-5}	1.86×10^{-5}	3.41×10^{-5}	0.00041	4.11×10^{-5}
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
ID FE	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637	1,867,637

Notes: Outcome: Doctor's appointment by diagnosis (icd code) in a given month. Regressions do not include control variables. Standard errors are clustered at 3-digit occupation level and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

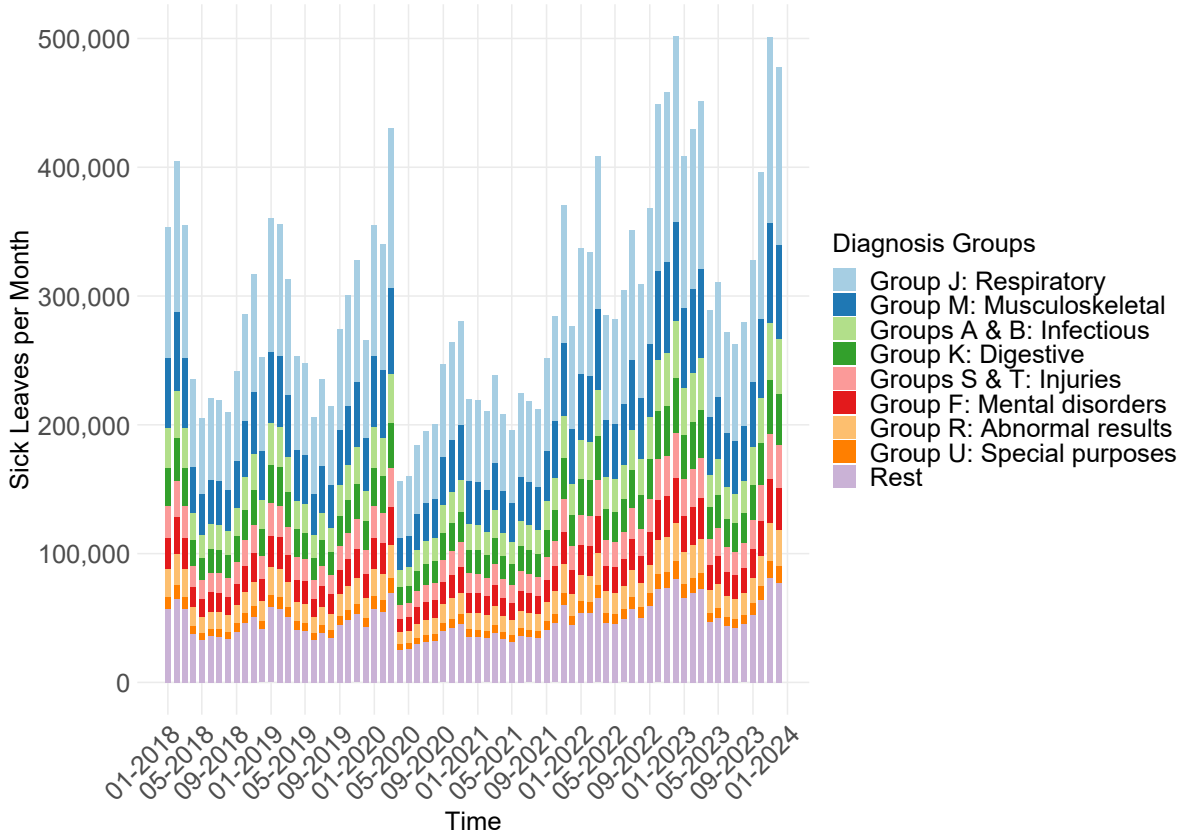
Table B.5: Effects on Hospital Stays by Diagnosis

	(1) All	(2) J	(3) M	(4) F	(5) S & T	(6) A & B	(7) K	(8) R	(9) U	(10) Other
WFH Probability										
× Dummy 2020	-0.00023	-4.1×10^{-5}	-0.00013***	-1.49×10^{-5}	3.93×10^{-5}	3.9×10^{-6}	2.35×10^{-5}	6.85×10^{-5}***	1.23×10^{-6}	-9.71×10^{-5}
	(0.00018)	(2.94×10^{-5})	(4.59×10^{-5})	(5.68×10^{-5})	(3.78×10^{-5})	(1.44×10^{-5})	(5.32×10^{-5})	(2.05×10^{-5})	(1.44×10^{-6})	(0.00015)
× Dummy 2021	-0.00047***	-9.39×10^{-5}***	-0.00026***	-9.27×10^{-5}	4.81×10^{-5}	-1.54×10^{-5}	1.11×10^{-7}	3.14×10^{-5}	4.1×10^{-7}	-1.97×10^{-6}
	(0.00018)	(3.55×10^{-5})	(6.01×10^{-5})	(7.21×10^{-5})	(3.75×10^{-5})	(1.44×10^{-5})	(4.54×10^{-5})	(3.16×10^{-5})	(9.21×10^{-7})	(0.00014)
× Dummy 2022	-0.00116***	-4.54×10^{-5}	-0.00021***	-0.00015*	-4.08×10^{-5}	-2.75×10^{-6}	-7.24×10^{-6}	5.57×10^{-5}**	8.01×10^{-18}	-0.00057***
	(0.00022)	(2.77×10^{-5})	(4.02×10^{-5})	(8.06×10^{-5})	(2.87×10^{-5})	(1.83×10^{-5})	(4.38×10^{-5})	(2.19×10^{-5})	(3.17×10^{-16})	(0.00019)
× Dummy 2023	-0.00179***	-7.22×10^{-5}***	-0.00033***	-0.00030***	1.31×10^{-5}	-1.12×10^{-5}	-3.68×10^{-5}	6.45×10^{-5}***	2.86×10^{-8}	-0.00080***
	(0.00033)	(2.66×10^{-5})	(3.74×10^{-5})	(8.46×10^{-5})	(3.84×10^{-5})	(1.84×10^{-5})	(5.17×10^{-5})	(2.18×10^{-5})	(3.87×10^{-8})	(0.00029)
Mean dep. var.	0.01326	0.00050	0.00119	0.00134	0.00081	0.00026	0.00135	0.00050	$NaN\times10^{-Inf}$	0.00575
Observations	134,767,512	134,767,512	134,767,512	134,767,512	134,767,512	134,767,512	134,767,512	134,767,512	134,767,512	134,767,512
R^2	0.04669	0.02319	0.03036	0.07613	0.02223	0.02118	0.03122	0.01886	0.03925	0.03715
Within R^2	2.31×10^{-6}	1.83×10^{-7}	8.57×10^{-7}	5.58×10^{-7}	7.49×10^{-8}	1.44×10^{-8}	1.64×10^{-8}	1.24×10^{-7}	8.04×10^{-8}	1.25×10^{-6}
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
ID FE	1,871,771	1,871,771	1,871,771	1,871,771	1,871,771	1,871,771	1,871,771	1,871,771	1,871,771	1,871,771

Notes: Outcome: Hospital stay by diagnosis in a given month. Regressions do not include control variables. Standard errors are clustered at 3-digit occupation level and reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

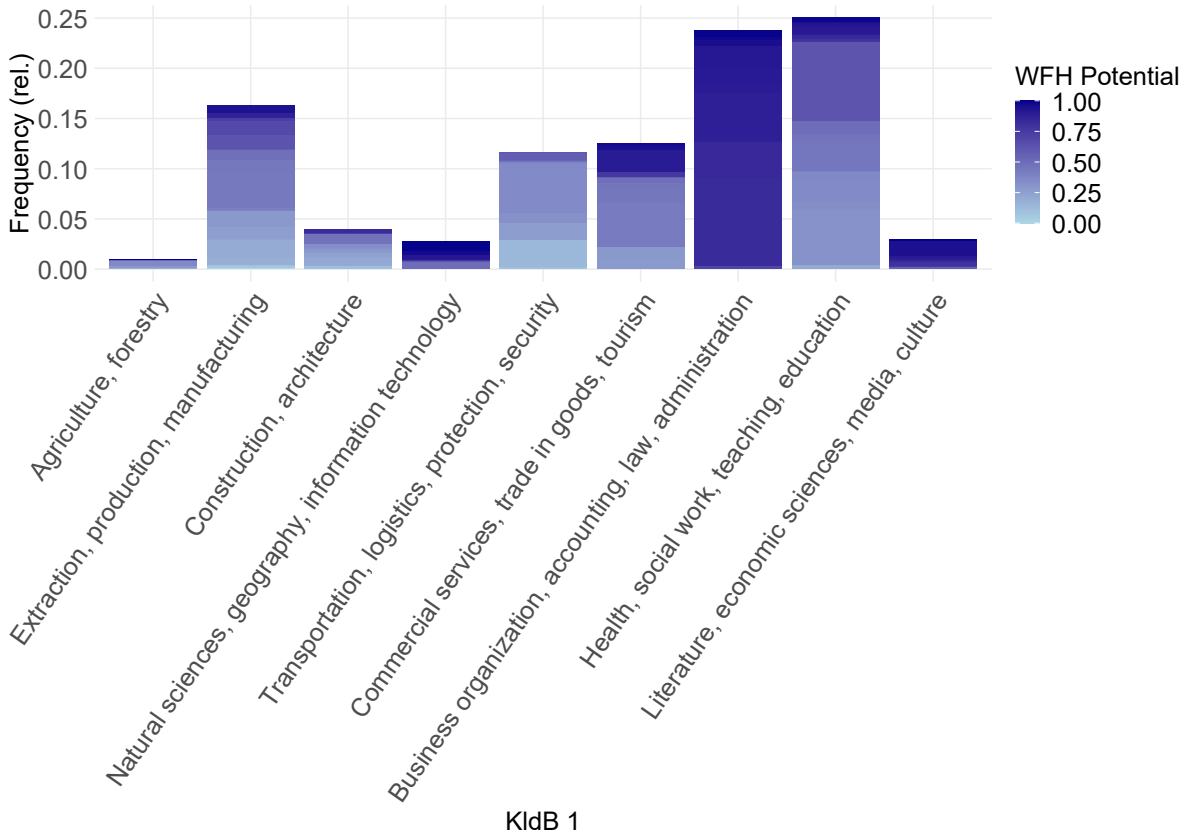
Appendix C Figures

Figure C.1: Number of Individuals on Sick Leave per Month by the Main Diagnosis



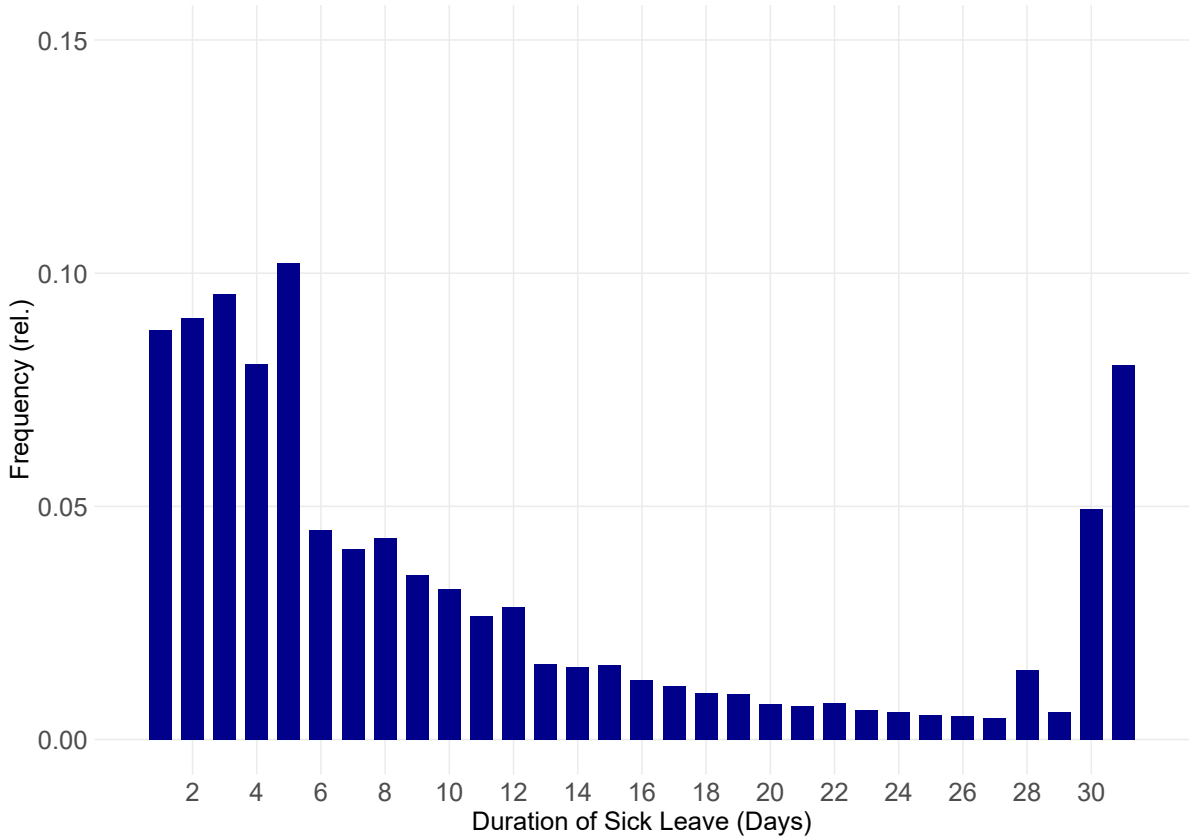
Notes: Sample restricted to individuals employed on February 15, 2020 and aged 26–55. The figure shows the number of individuals with at least one sick leave certificate (Arbeitsunfähigkeitsbescheinigung - AU) in a given month, according to the main diagnosis.

Figure C.2: WFH Feasibility by Occupation



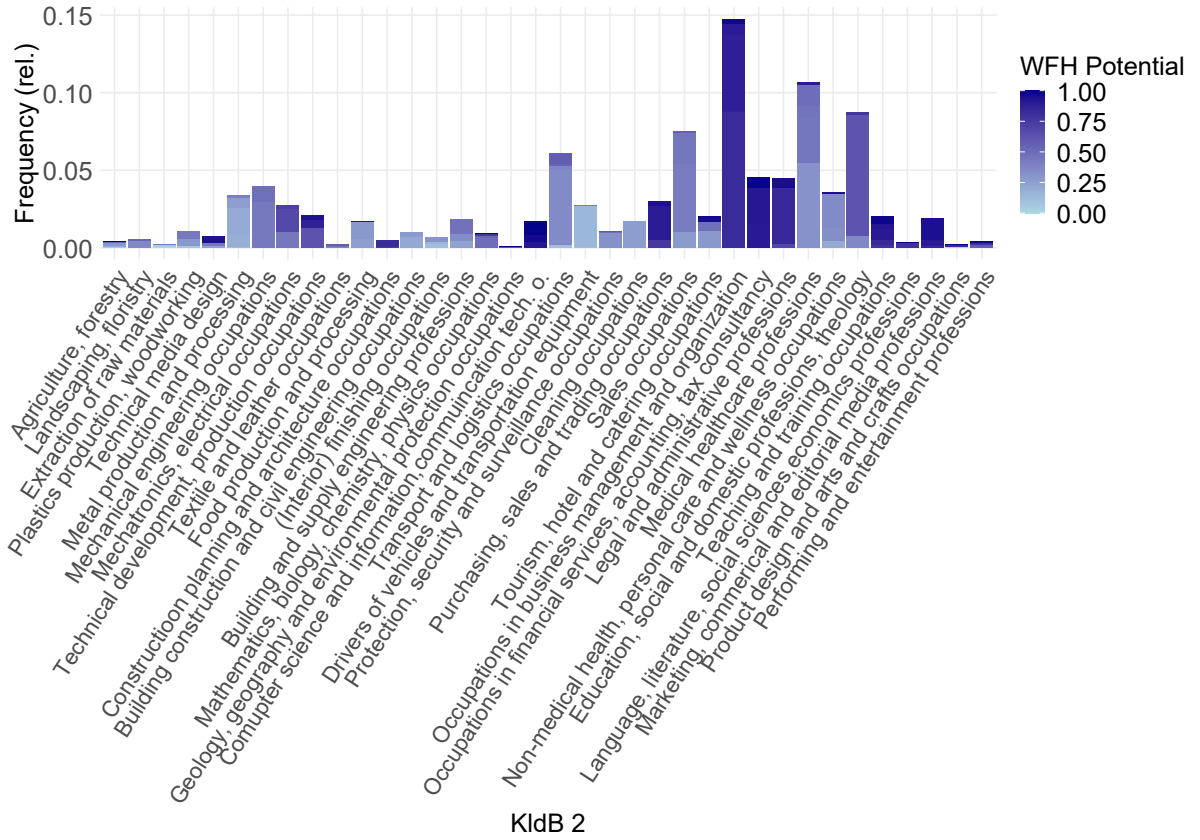
Notes: Sample restricted to individuals employed on February 15, 2020 and aged 26–55. The figure shows the distribution of the work-from-home (WFH) feasibility index across the one-digit occupational groups of the German Classification of Occupations (KldB 2010).

Figure C.3: Sick Leave by Duration in Days



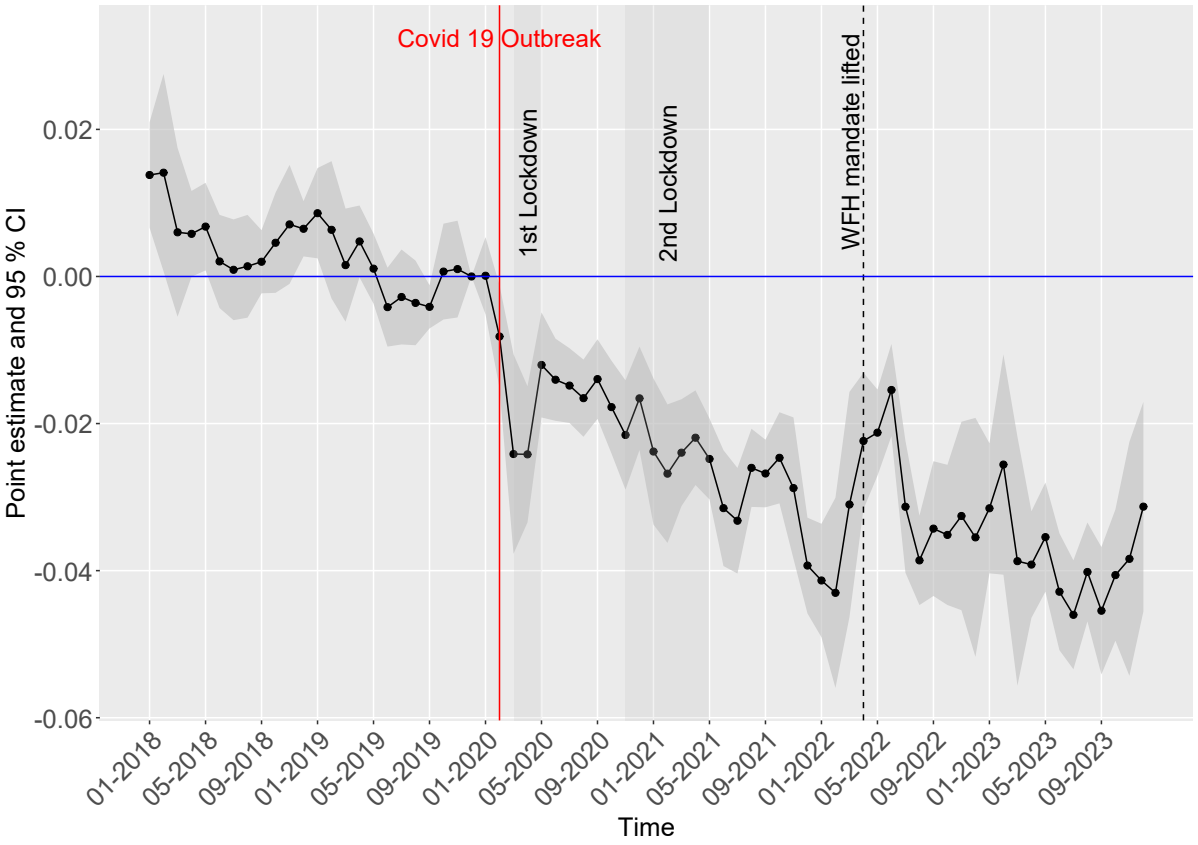
Notes: The figure shows the frequency of a given sick leave duration among all individuals with at least one sicke leave certificate (*Arbeitsunfähigkeitsbescheinigung* - AU) in a given month. Sample restricted to individuals employed on February 15, 2020 and aged 26–55.

Figure C.4: WFH Potential (at 3 digit level) for occupations (at 2 digit level of German Classification of Occupations (KldB 2))



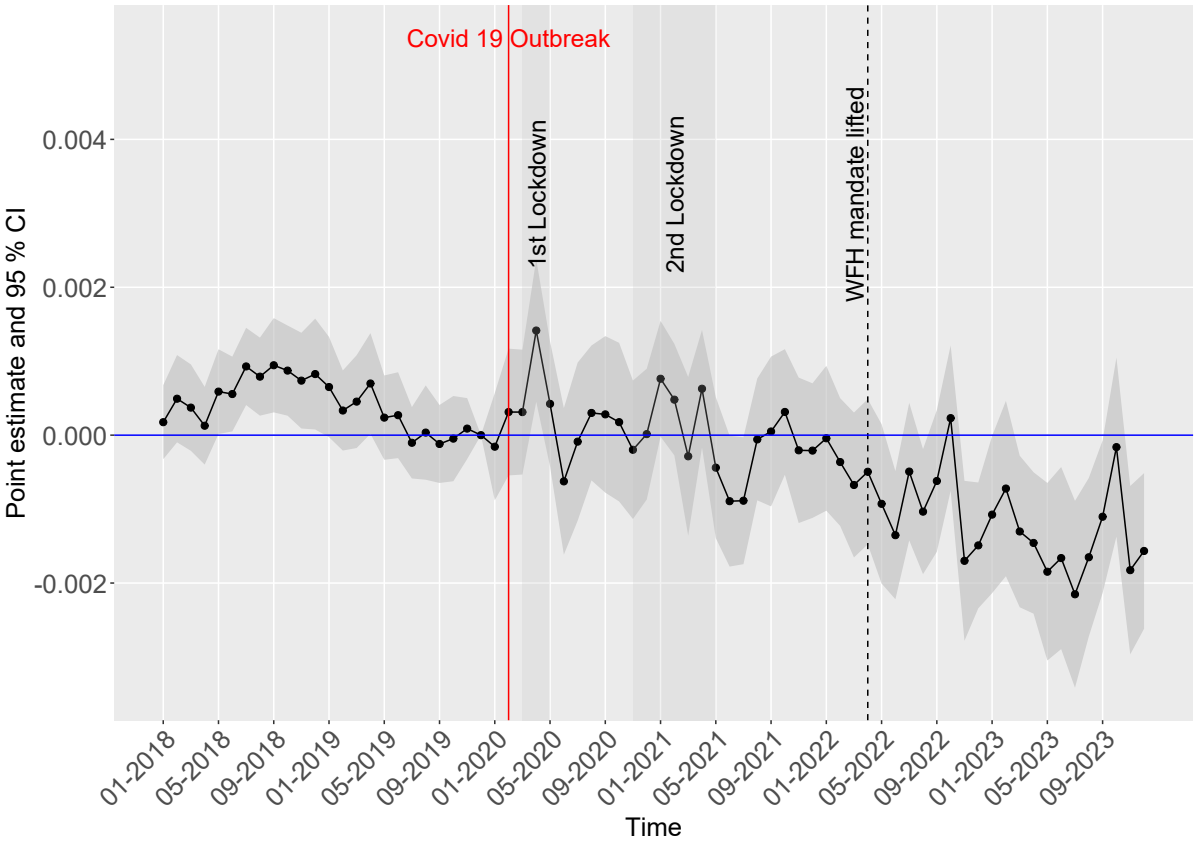
Notes: ...

Figure C.5: Event Study: Effects on the Probability of Sick Leave (prior to de-seasoning)



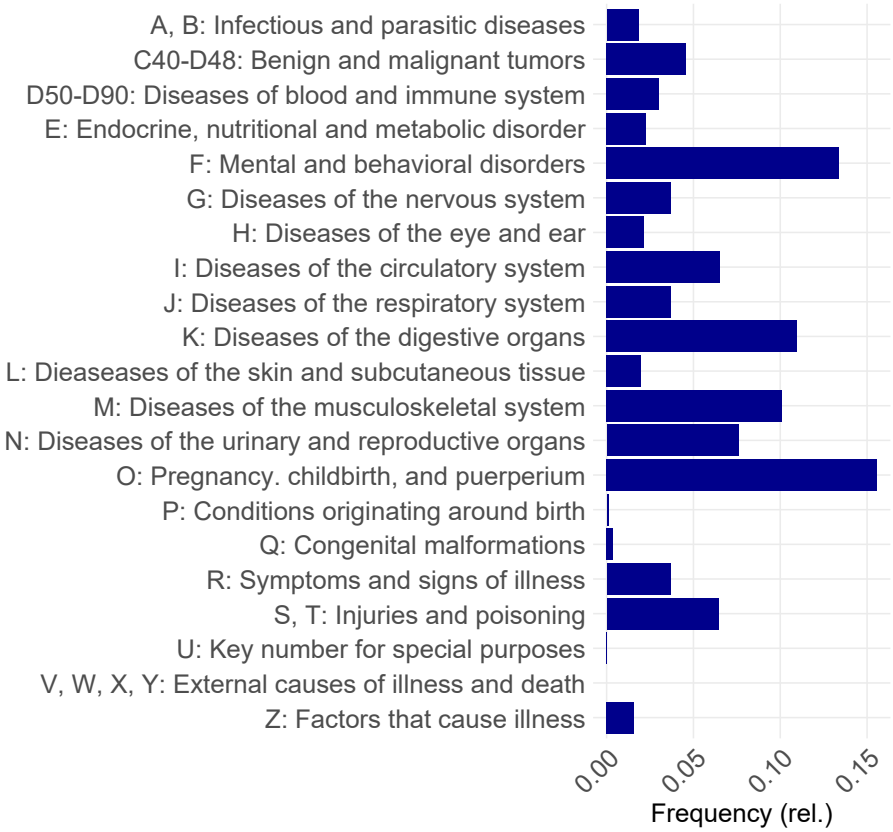
Notes: The figure presents DiD results based on Equation 1. The outcome variable is a dummy equal to one in months in which a worker files a sickness leave. The sample is a balanced panel of employed individuals aged 26–55 as of February 15, 2020, observed monthly from 01/2018 to 12/2023. Mean dependent variable is calculated over the 2018–2019 pre-treatment period. Confidence intervals are drawn at the 95% level using standard errors clustered by 3-digit occupation.

Figure C.6: Event Study: Effects on the Probability of a Hospital Stay (de-seasonalized)



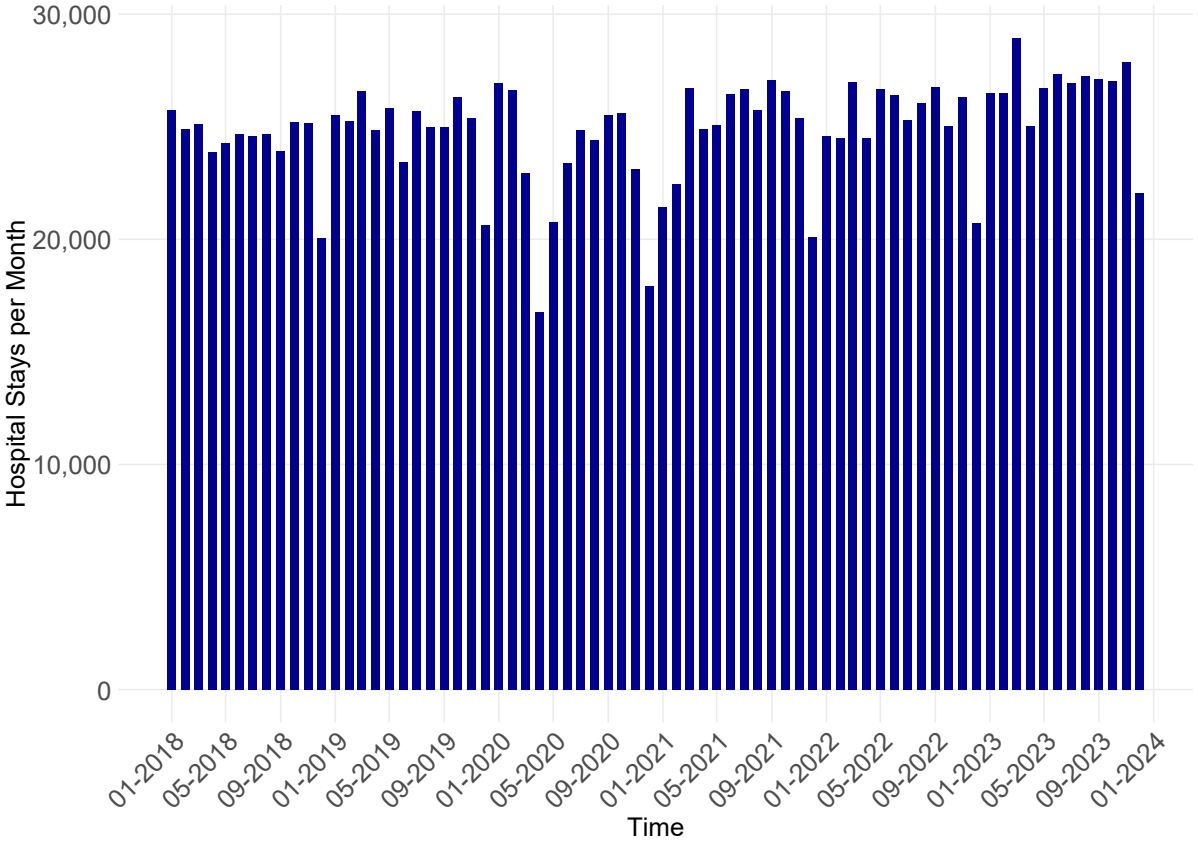
Notes: The figure presents DiD results based on Equation 1. The outcome variable is a dummy equal to one in months in which a worker is at the hospital. The sample is a balanced panel of employed individuals aged 26–55 as of February 15, 2020, observed monthly from 01/2018 to 12/2023. Mean dependent variable is calculated over the 2018–2019 pre-treatment period. Confidence intervals are drawn at the 95% level using standard errors clustered by 3-digit occupation.

Figure C.7: Frequency of Diagnosis in Hospital



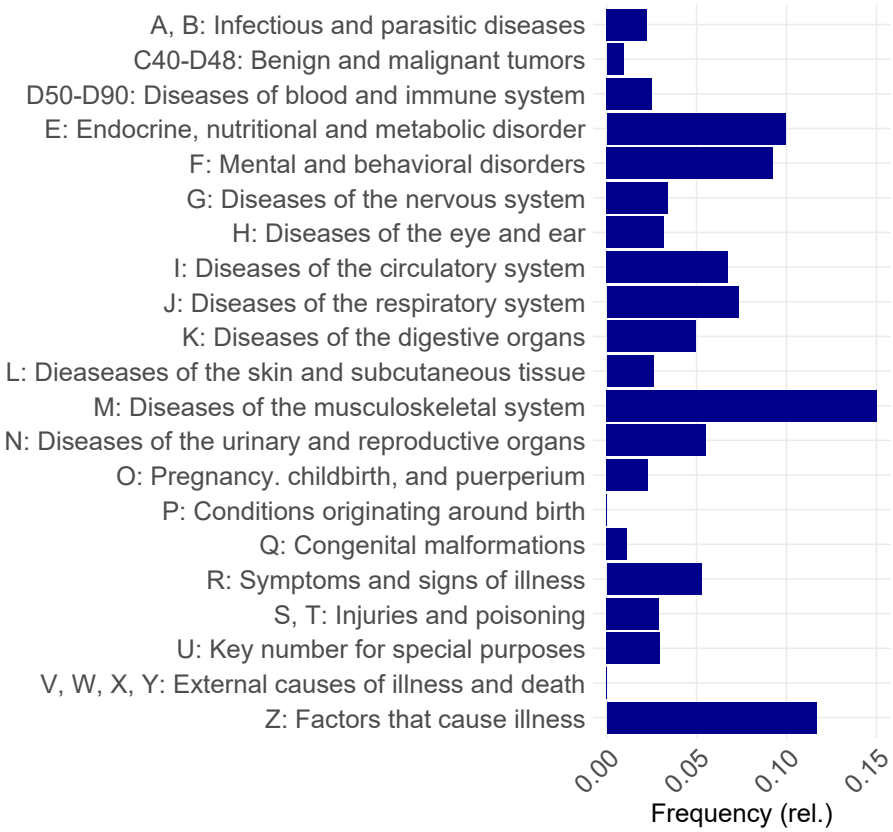
Notes: ...

Figure C.8: Number of Hospitals Stays by Gender)



Notes: ...

Figure C.9: Frequency of Diagnosis - Doctor's Appointment)



Notes: ...

Figure C.10: Number of Doctor's Appointments by Gender)

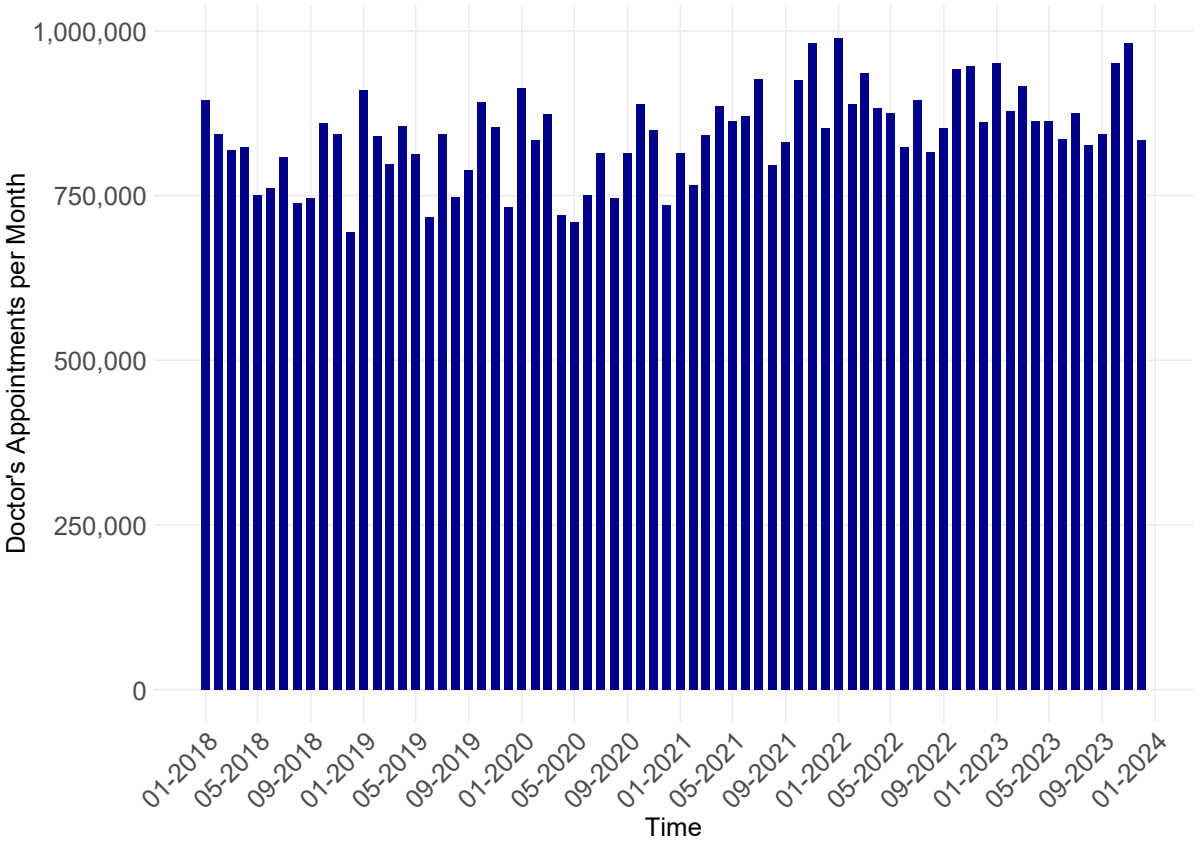
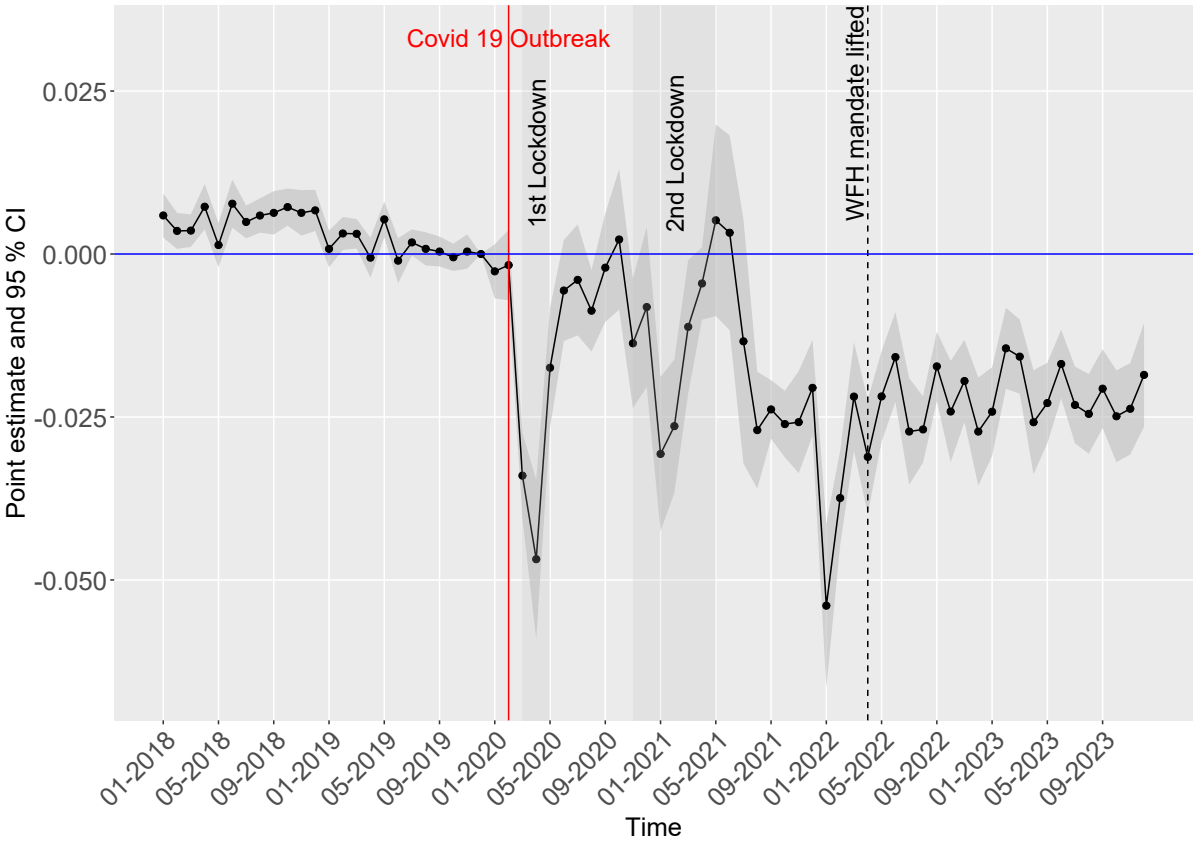
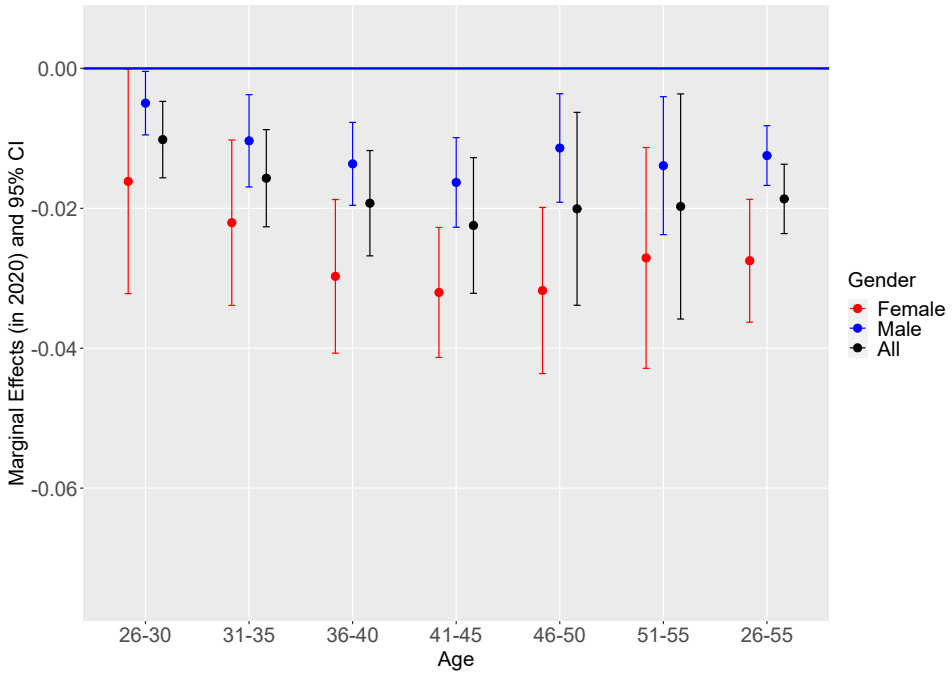


Figure C.11: Event Study: Effects on the Probability of a doctor's appointment (de-seasonalized)



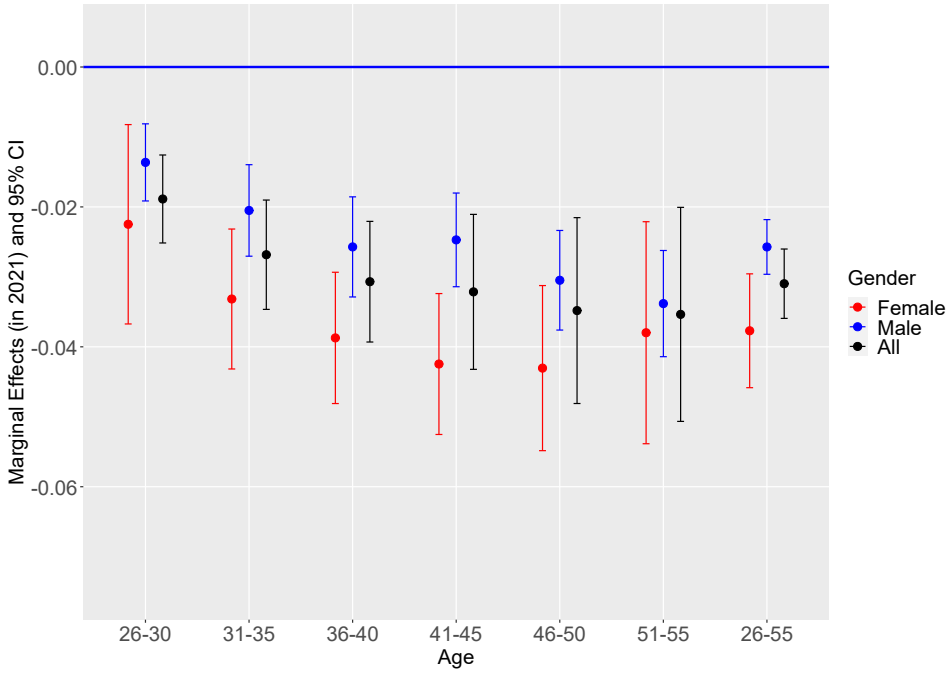
Notes: The outcome variable is a dummy equal to one in months in where an appointment happened. The sample is a balanced panel of employed individuals aged 26–55 as of February 15, 2020, observed monthly from 01/2018 to 12/2023. Mean dependent variable is calculated over the 2018–2019 pre-treatment period. Confidence intervals are drawn at the 95% level using standard errors clustered by 3-digit occupation.

Figure C.12: Sickness Leaves by Age and Gender, 2020



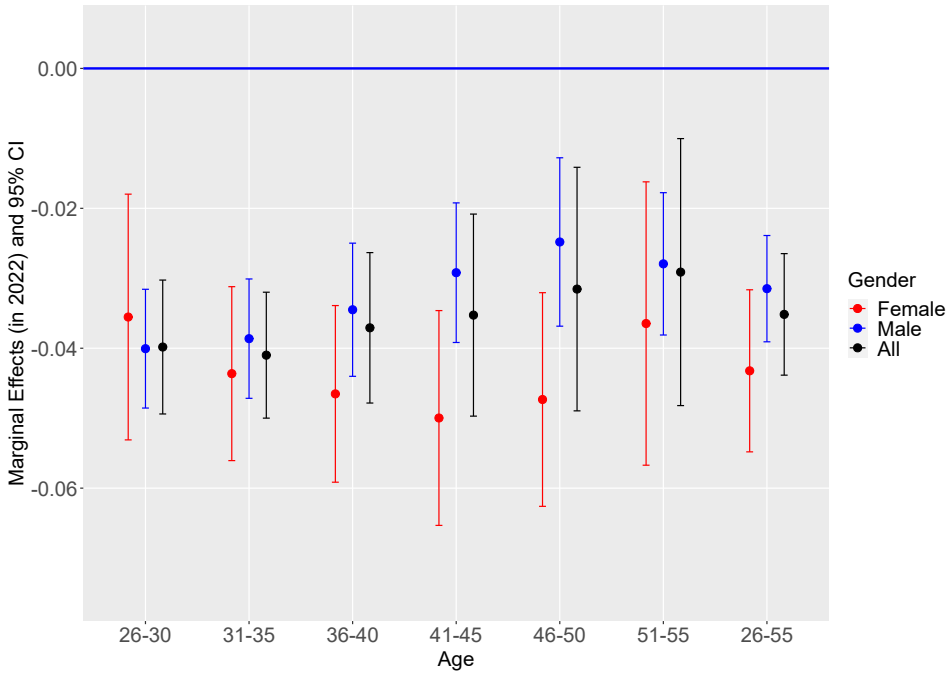
Notes:

Figure C.13: Sickness Leaves by Age and Gender, 2021



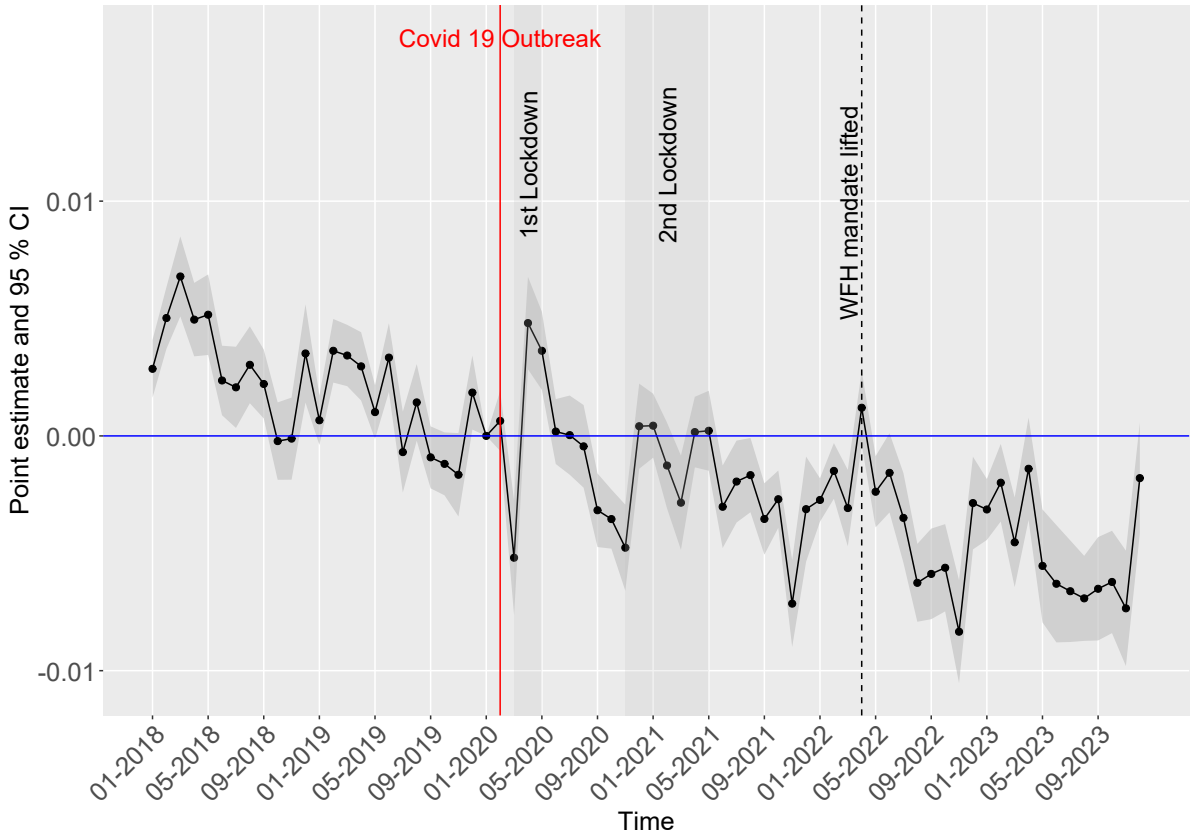
Notes:

Figure C.14: Sickness Leaves by Age and Gender, 2022



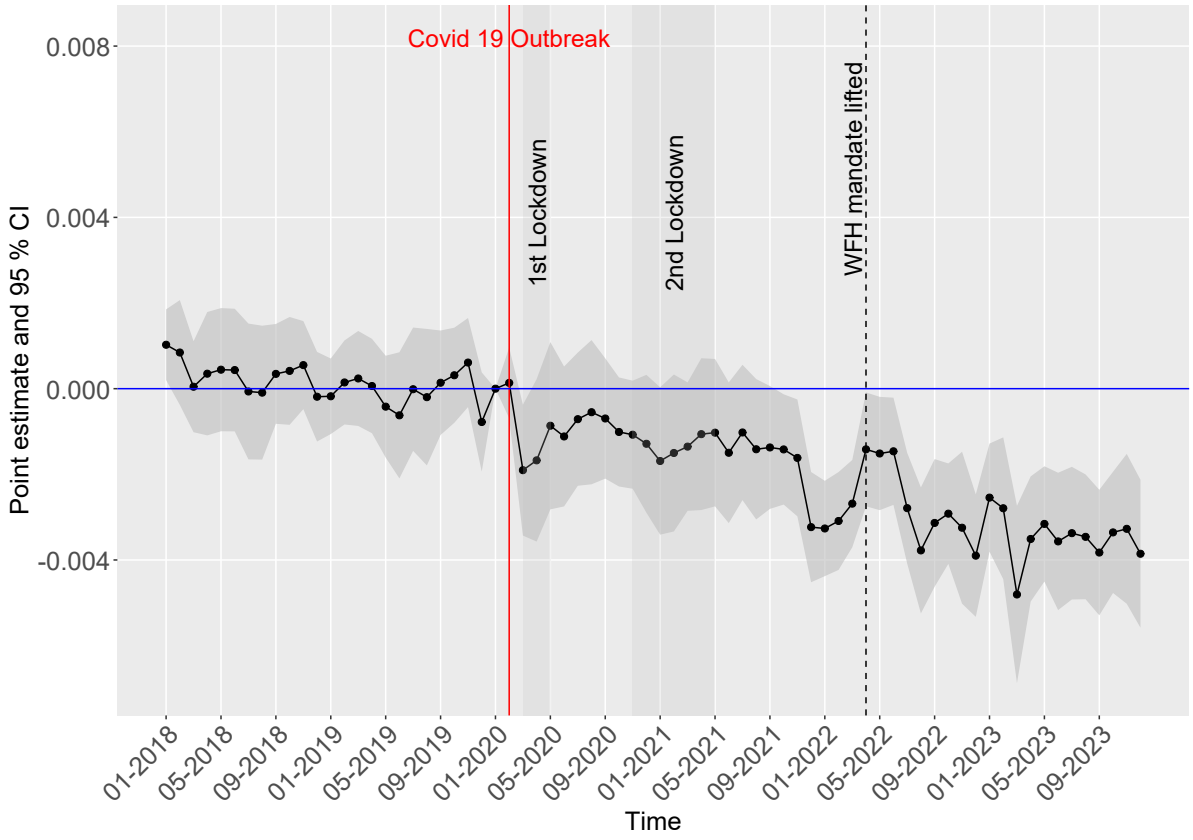
Notes:

Figure C.15: Event Study for M: Diseases of the musculoskeletal system



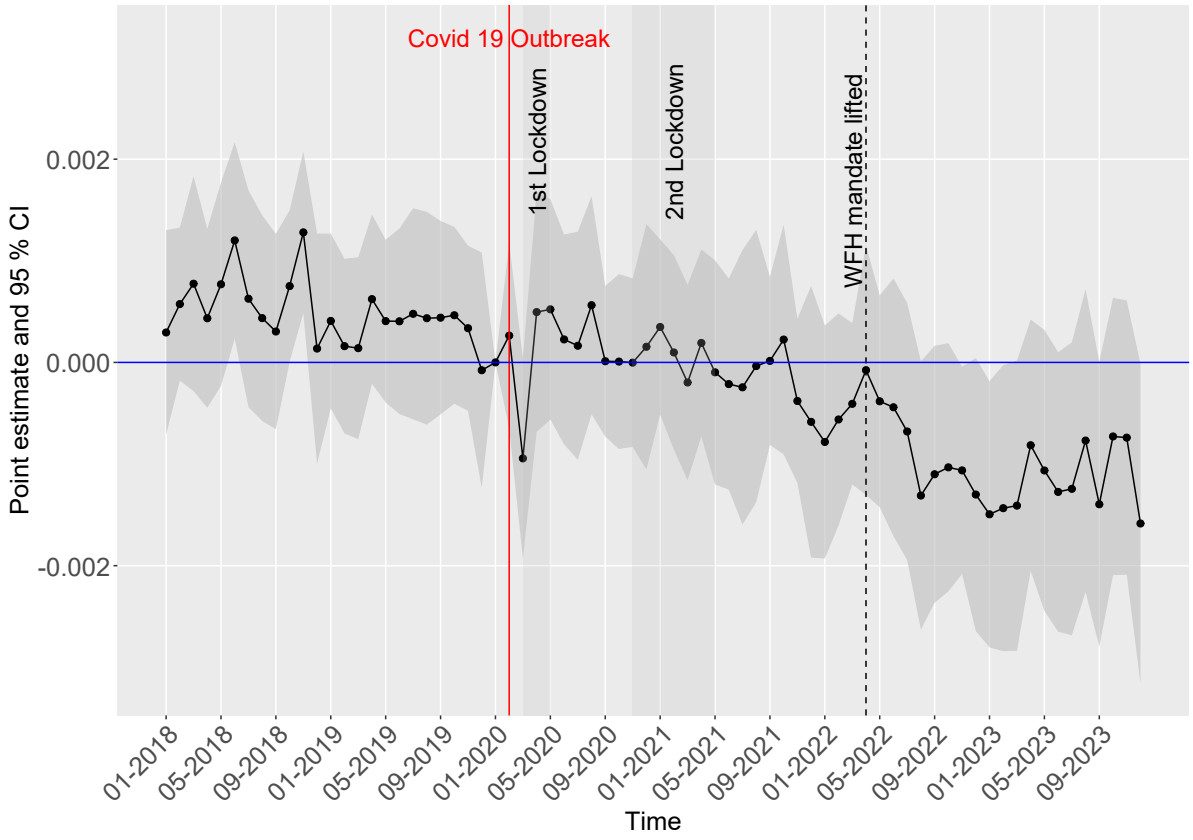
Notes: ...

Figure C.16: Event Study for A, B: Infectious and parasitic diseases



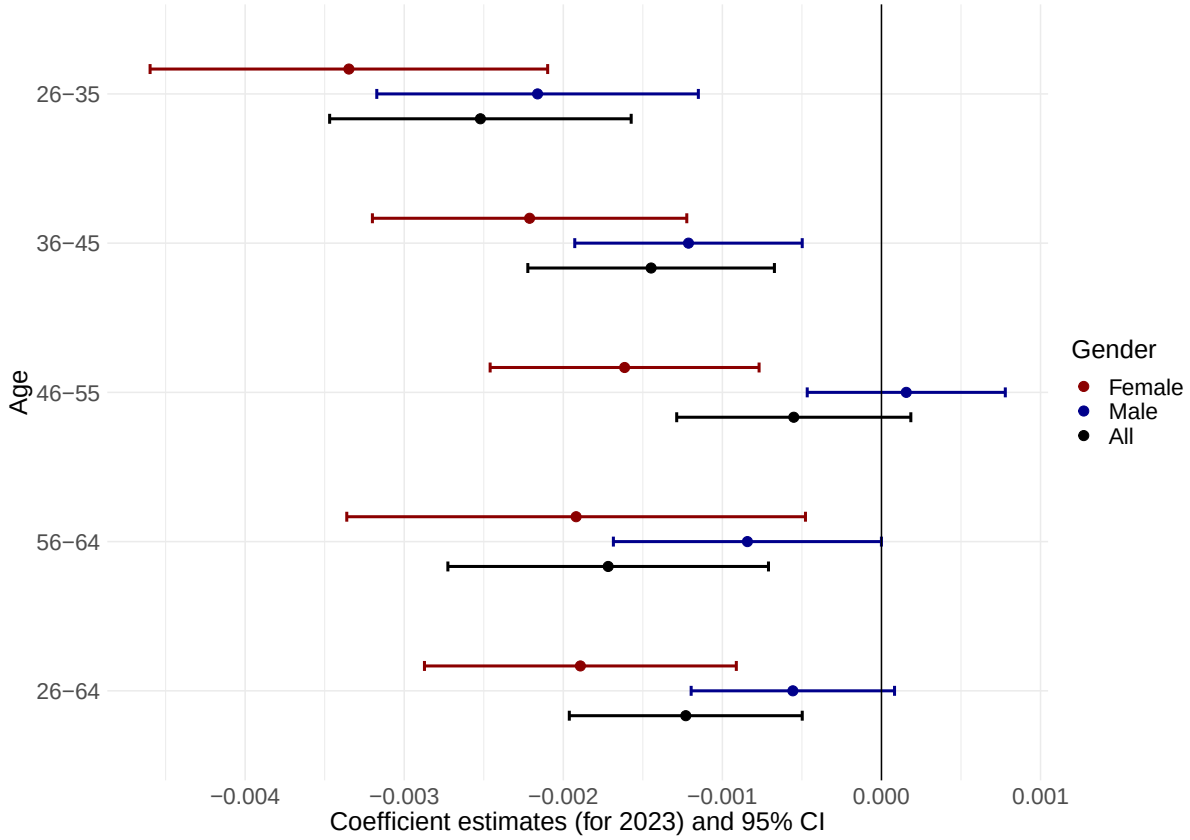
Notes: ...

Figure C.17: Event Study for K: Diseases of the digestive organs



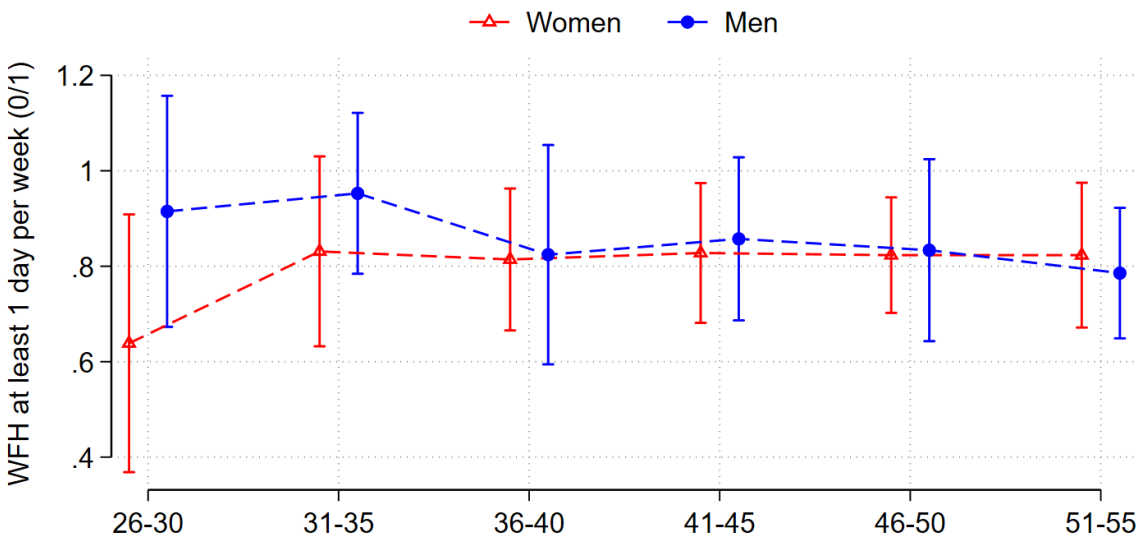
Notes: ...

Figure C.18: Sickness Leaves per Age and Gender for ICD F



Notes: ...

Figure C.19: Effects of WFH potential on WFH status in 2023 by gender and age (SOEP data)



Notes: The figure OLS estimates of 2019 WFH potential [0,1] on WFH status in 2023 by gender and age groups. WFH status is a dummy for working remotely at least one day per week in 2023. The sample includes individuals employed and aged 26–55 in 2019. 95% confidence intervals are calculated using standard errors clustered by 3-digit occupation. Data are from the Socioeconomic Panel (SOEP, Version 40.1).