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An initiative for a more inclusive working life and its effect on return-to-work after sickness absence: a multistate longitudinal cohort study

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ABSTRACT

Objectives To reduce sickness absence (SA) and increase work participation, the tripartite Agreement for a More Inclusive Working Life (IA) was established in Norway in 2001. IA companies have had access to several measures to prevent and reduce SA. Our aim in this paper was to estimate the average effect of having access to IA at the time of entering a first SA on later return-to-work (RTW) and on time spent in other work-related states. A secondary objective was to study how effects varied between women and men, and individuals with SA due to either musculoskeletal or psychological diagnoses.

Design Population-based observational multistate longitudinal cohort study.

Setting Individual characteristics and detailed longitudinal records of SA, work and education between 1997-2011 were obtained from population-wide registries.

Participants Each individual born in Norway 1967–1976 who entered full-time SA during 2004–2011, with limited earlier SA, was included (n=187 930).

Primary and secondary outcome measures Individual multistate histories containing dated periods of work, graded SA, full-time SA, non-employment and education.

Methods Data were analysed in a multistate model with 500 days of follow-up. The effect of IA was assessed by estimating differences in state probabilities over time, adjusted for confounders, using inverse probability weighting.

Results IA increased the probability of work after SA, with the largest difference between groups after 29 days (3.4 percentage points higher (95% CI 2.5 to 4.3)). Differences in 1-year expected length of stay were 8.4 additional days (4.9 to 11.9) in work, 7.6 (4.8 to 10.3) fewer days in full-time SA and 1.6 (-0.2 to 3.4) fewer days in non-employment. Similar trends were found within subgroups by sex, musculoskeletal and psychological diagnoses. The robustness of the findings was studied in sensitivity analyses.

Conclusion Measures to prevent and reduce SA, as given through IA, were found to improve individuals' RTW after entering SA.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ This is the first study on the effects of the Norwegian population-wide initiative to increase work-participation that analyses a large dataset of longitudinal multistate outcomes.
⇒ The data exhibit a high level of completeness and include also detailed covariate information.
⇒ Limitations of the study are that we only had access to observational data and that Agreement for a More Inclusive Working Life was not randomised.

INTRODUCTION

Sickness absence (SA) from work is an important long-term health outcome for the individual, as well as a social and financial burden for society.[1–3] It has been shown that while in SA, individuals are at greater risk of a more permanent exit from working life.[4 5] SA increased greatly in Norway between 1995 and 2000, mainly due to an increase in long-term SA (more than 16 calendar days). The yearly average days of SA per worker in private workplaces, increased from 8.8 days to 12.9 days in the same period.[6] It should be noted that this increase came after a period of reduction in SA,[7] and that around one-third of the increase can be explained by changes in the size and age of the workforce.[6]

In 2001, the Norwegian Government reached out to major partners in working life, representing both workers and employers, with the intention of reducing SA and prolonging working life. This resulted in the tripartite Agreement for a More Inclusive Working Life (IA), which is still active, and included three operative goals: (1) reduce SA by at least 20 %, (2) increase employment for individuals with functional limitations and (3) increase the average retirement age.[6] By 2004, 55% of workers were in IA companies, that is, companies that signed a cooperation agreement with the Norwegian Labour and Welfare Administration (NAV) and the employee representatives in the company, to cooperate systematically to achieve more inclusive workplaces.[8]

IA companies and their employees have access to several measures to reduce and prevent SA. These include special regulations and support from working life centres that were established regionally by NAV. The support from these centres can be comprehensive, including tailored support for employees with health problems.[9] The measures included the possibility for employees in SA to use so-called active sickness benefits, where they may return-to-work (RTW) and perform modified tasks while still receiving payments from NAV. Employees in IA companies are also allowed to have longer self-certified SA (up to eight consecutive calendar days, instead of three, and a total of 24 annual days, instead of 12). The IA companies may receive refunds for measures related to aiding employees in returning to work. If it is impossible for an employee to return to the same position they had before SA, the IA companies have agreed to cooperate with NAV in assisting in retraining so that the employee can continue to work in the same company.

Since implemented, IA has not met the goals regarding SA, and systematic evaluations, although sparse, suggest limited or no effect on the risk of experiencing SA.[8 10–12] Studies of other general workplace interventions have found that they were generally not effective in reducing SA.[13] However, there are studies suggesting effects of workplace interventions on RTW.[12 14]

The main objective of this study was to estimate the average effect of having access to IA at the time of entering a first SA on later RTW and on time spent in other work-related states for the following 500 days. To analyse such individual outcome trajectories in more detail than have been done before, we used a multistate model,[15] capturing individuals' movement between the states of full-time SA, graded SA, work, non-employment and education over time. Inverse probability of treatment (IPT) weighting was used to adjust for confounding between IA and multistate outcomes.[16] The effect of IA has not previously been studied in detail at a population level using such methods. A secondary objective was to study how effects varied between women and men, and individuals with SA due to either musculoskeletal or psychological diagnoses.

METHODS

Design, participants and exposure

To meet the study objectives, we used observational longitudinal registry data from a cohort consisting of all individuals born in Norway between 1967 and 1976 (626 928 individuals), as registered by the Medical Birth Registry of Norway. The same cohort is described in greater detail by Kristensen and Bjerkedal.[17] Given limited earlier SA (no SA in 2003), individuals were included in the analysis

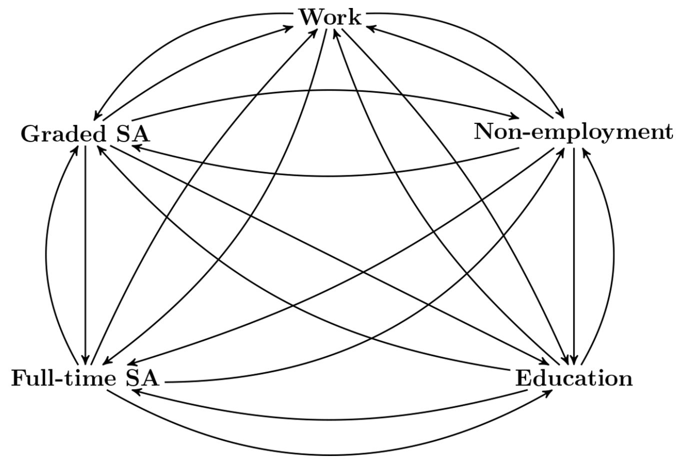

Figure 1 The multistate model showing possible transitions after individuals start in in full-time sickness absence (SA). Individuals may move repeatedly between full-time SA, graded SA, work, non-employment and education. Note that death was a competing transition in all states, but left out of the figure.

if they entered full-time SA (>16 calendar days, counted from the first day), between 1 January 2004, when IA was properly implemented, and 31 December 2010. In total, this comprised 187 930 persons. Baselines were set to the dates of the initial SA episode for all individuals, who simultaneously had their IA exposure (yes/no) recorded, based on the IA status of the company they worked for, and were followed for 500 days or until death, right-censoring or administrative censoring on 1 January 2011. The choice of 500 days was a pragmatic choice, meant to cover the first full year and a short period beyond. The immediate period after the first year is of interest, as welfare policies impose a change in benefits received after a full year of receiving sick leave benefits. Moreover, for even longer follow-up periods, individuals' IA status would be more likely to change, making results from an analysis based on baseline IA status more difficult to interpret.

Patient and public involvement

Patients or the public were not involved in the design, or conduct, or reporting, or dissemination plans of our research.

Outcomes and confounders

The individual multistate histories are described by dated transitions between periods of work, graded SA, full-time SA, non-employment, education and death, referred to as states, as shown in figure 1. Multistate models can be seen as extensions of standard time-to-event models with only two states, such as alive and dead. In multistate models, individuals are allowed to have several transitions while remaining under observation. In our application, individuals started in full-time SA and could move back and forth between transient states at any time during the 500 days follow-up period, and for example have multiple spells of full-time SA. The exception is death, which is a so-called absorbing state, where further transitions are not possible.

As the IA Agreement is not randomly assigned to individuals, the association between IA and the individual multistate histories may be confounded by various characteristics that are different between individuals and workplaces with and without IA and need to be adjusted for. For this purpose, information was collected at individual level on the assumed confounders recorded at individuals' baseline: age, sex, education level, calendar year, company size, geographical region and type of industry. Education level was the individual's highest attained degree, separated into four categories: lower secondary, upper secondary, undergraduate and graduate. Type of industry covered 20 categories in the Statistical Classification of Economic Activities in the European Community.[18] Company size was based on yearly records of number of employees, and company region comprised southern, eastern, western, middle and northern parts of Norway.

Data sources and data preparation

All the data were collected from Statistics Norway's event database of employment and welfare (FD-Trygd), The National Education Database and the registers of the NAV. The data contained individual and company characteristics acting as potential baseline confounders, individual status of the main intervention (IA status), dated records of all individuals' work (with taxable income), SA (>16 calendar days) and education. From the records of work, SA and education, we generated individual multistate outcome histories, or trajectories, over a period of 500 days, with the possible states of full-time SA, graded SA, work, education and non-employment.

Individuals were included in the study on the date of their first full-time SA episode after 1 January 2004, given that they had not been in SA the previous year. All the baseline confounders were set to the values as recorded on each individual inclusion date. IA status was set to the IA status of the individual's company at the time of inclusion. Individuals working for more than one company during follow-up were seen as having IA if either of the workplaces had IA. For this study, SA included periods eligible for either of three different types of benefits in the Norwegian welfare system: sick leave benefit, work assessment allowance (medical or vocational rehabilitation benefits) and disability pension, all attainable as full-time (100%) or graded (<100%). Work referred to paid employment and included holidays and parental leave, while education covered admittance to officially licensed education programmes. Periods without SA, work or education were considered as non-employment if they had later records of SA, work or education. Lost to follow-up without any later records were treated as right-censoring. Whenever different types of records occurred simultaneously on the same dates for an individual, different records had precedence in the following order, from most to least important: SA, work and lastly education.

Subgroup and sensitivity analyses

In addition to the main analysis, separate analyses were done for women and men, and for diagnosis group associated with initial SA (musculoskeletal or psychological). Musculoskeletal diagnoses consisted of ICPC-2 (International Classification of Primary Care)[19] codes starting with L, while psychological diagnoses referred to codes starting with P.

We conducted five sensitivity analyses. First, we compared results adjusting for subsets of the confounders, to see how omitted variables in the adjustment set could bias results. In the second, we adjusted for additional potential confounders available for a male subgroup of the study population, describing IQ, physical stamina, BMI and eligibility for military service. In the third, we used pre-baseline longitudinal outcomes between 1997 and 1999, as negative outcome controls.[20] If confounding was sufficiently adjusted for, state transition histories before baseline should be similar across IA groups, after weighting with the same IPT weights as in the main analysis. In the fourth, we analysed a subset of industries with mostly private companies. Lastly, since our study population were in the age span 28–43 at entry into the study, and a substantial part (20,355) of the initial SA cases was in connection with pregnancy, childbearing and family planning (ICPC-2 codes starting with W), an analysis where these cases were removed was conducted.

Although type of industry is adjusted for in the main analysis, we also created sequence plots of individuals' multistate histories within five different industry sectors for descriptive purposes. These plots illustrate typical patterns of multistate trajectories at the individual level, over the 500 days of follow-up. We also looked at gender balance within the largest industries of our study population for discussion purposes.

A closer description of these analyses is found in online supplemental material 1.

Estimands and statistical methods

The individual multistate outcomes were analysed using hazard based multistate models for time-to-event data,[15] by first fitting hazard models for each transition and then estimating state probabilities for all states in figure 1. The model allows individuals to move, possibly back and forth, between states over time according to the possible transitions illustrated in the figure. By state probabilities, we here mean the probability of being in a particular state at a given time-point, which can be seen as an extension of regular survival probabilities (eg, Kaplan-Meier curves). To assess the effect of IA, we sought to identify the average treatment effect, as the difference in state probabilities $\theta(t) = \pi^1(t) - \pi^0(t)$, where $\pi^a(t)$ is the adjusted marginal state probability, corresponding to the state probability we would have seen if everyone in the target population was fixed to having IA status equal to a (taking the values 1 and 0 for IA and no IA, respectively). From the state probabilities, we also calculated the expected length of stay (ELOS)[21] in the different states over the first year, for the situations where everyone was fixed to a=1 or a=0.

Confounding adjustment was done by calculating baseline stabilised IPT weights,[22] also known as propensity score weights, and then fitting weighted additive hazards regression models[23] for every possible transition in figure 1, adjusting only for IA status. This corresponds to using weighted Nelson-Aalen estimators for the cumulative hazards separately for the two IA groups. The corresponding state probabilities were then estimated by plugging the transition-specific cumulative hazard estimates into the Aalen-Johansen estimator. The ELOS can be calculated directly from the Aalen-Johansen estimates, as the area under the curve of the corresponding state probabilities over time. To calculate the IPT weights, we modelled IA status as a function of the baseline confounders in a logistic regression model. Since IA is an intervention at the company level, we calculated 95% CIs using a clustered bootstrap where the resampling is done on company level.[24]

For a more formal specification of the target estimands and details on the statistical methods, see online supplemental material 1, and, more generally, Andersen and Keiding,[15] Gran *et al*[16] and Aalen *et al*.[23] All analyses were performed in R, on the Services for Sensitive Data facilities, owned by the University of Oslo. R code is available on GitHub (see the Declarations section).

RESULTS

Descriptive statistics

Over a total follow-up of 90 231 405 person days, the 187 930 individuals included made a total of 457 610 transitions, which are summarised in detail in online supplemental table 1. A summary of the individual characteristics can be found in table 1. In the second and third column of the latter table, we can see how the measured confounders are distributed differently among the IA and non-IA individuals, with, for example, more women and individuals in larger workplaces having IA. In the fourth and fifth column, however, we see how the measured confounders are distributed in the weighted data, after applying the IPT weights, with the measured confounding characteristics now being well balanced between groups.

First, we fitted a multistate model without covariates, to calculate the observed state probabilities in the entire cohort, regardless of IA status. A stacked probability plot is shown in figure 2. All individuals started in full-time SA and could thereafter move to other states. The proportion of individuals who had returned to work reached 50.6% (95% CI 50.4% to 50.8%) after 50 days, and 64.7% (95% CI 64.5% to 64.9%) after 100 days. Just before passing 1 year, 77.0% (95% CI 76.8% to 77.2%) were in work, 3.3% (95% CI 3.2% to 3.4%) were in graded SA and 9.9% (95% CI 9.8% to 10.0%) in full-time SA. At the same time, 9.2% (95% CI 9.0% to 9.3%) were in non-employment and 0.5% (95% CI 0.47% to 0.53%) in education. After 1 year, we see distinct shifts in the probabilities, coinciding with maximum allowed days of consecutive sick leave benefit. After this, individuals either RTW or typically receive other welfare benefits, including work assessment allowance.

Main analysis

To assess the effect of IA versus no IA, we compared state probabilities in an IPT weighted multistate model. A summary of individual characteristics in the weighted population can be found in table 1. Figure 3 shows the absolute difference in state probabilities for IA versus no IA over the follow-up period, with 95% CI's based on 1000 bootstrap samples. In the figures, death was left out, as differences here were negligible. The figure shows how IA increased the probability of RTW and decreased the probability of full-time SA in the period following an initial SA episode. Peak effect of IA on RTW occurred after 1 month, where the probability was about 3.4 percentage points (pp) higher with IA.

The difference declined to below 2 pp after one year. The effect on full-time SA followed an opposite pattern for the first 2–3 months and declined to zero after 1 year. The effect on graded SA was small (increase), but the confidence intervals included zero. The effect on non-employment was small initially, but amounted to around 1 pp reduction after 1 year.

The average individual effects of IA versus no IA are summarised in terms of ELOS in table 2. Here, we see that the estimated ELOS difference between IA and no IA for the first year was 8.4 more days (95% CI 4.9 to 11.9 days) in work, 7.6 (95% CI 4.8 to 10.3) fewer days in full-time SA and 1.6 (95% CI −0.2 to 3.4) fewer days in non-employment. Differences for graded SA and education were smaller.

Subgroup analyses

Results from the subgroup analyses are plotted in figure 3. Similar effect patterns as before were found, however, effects of IA were higher for men than for women. Effects were also higher in both selected diagnosis groups compared with in the overall analysis, although only slightly for musculoskeletal diagnoses.

For women, the effect of IA on RTW from full-time SA, reached a peak after 25 days, where the probability was 2.8 pp (95% CI 1.9 to 3.7) higher with IA. The effect remained close to 2 pp higher for roughly 200 days, before declining to around one pp 1 year after inclusion. After 1 year, the effect was close to zero. The effect on work was almost entirely offset by reduced probability of full-time SA, while effects on other states were smaller. The peak effect for men on RTW were 29 days after starting full-time SA, with 4.5 pp (3.0 to 6.0) higher probability for men with IA. Contrary to in women, the effect on work stayed positive, never dropping below 2 pp, the entire follow-up period. The effect on work was mostly offset by reduced probability of full-time SA, but with more noticeable effects on other states, compared with women. There was a small increase in graded SA (after initially starting

Table 1 Descriptive statistics for individuals working in companies with the Inclusive working life Agreement (IA), or without, at the time of inclusion. The table also describes the inverse probability of treatment weighted population.

	No IA, n (%)	IA, n (%)	No IA (IPTW) n (%)	IA (IPTW) n (%)
Sex				
Women	57 002 (0.48)	45 139 (0.66)	63 383 (0.53)	37 907 (0.55)
Men	62 361 (0.52)	23 428 (0.34)	55 037 (0.46)	30 885 (0.45)
Age at inclusion				
28–32	33 876 (0.28)	16 336 (0.24)	31 722 (0.27)	18 619 (0.27)
33–37	60 561 (0.51)	34 485 (0.50)	60 150 (0.50)	35 121 (0.51)
38–43	24 926 (0.21)	17 746 (0.26)	26 547 (0.22)	15 052 (0.22)
Inclusion year				
2004	31 255 (0.26)	12 762 (0.19)	28 556 (0.24)	17 376 (0.25)
2005	25 935 (0.22)	12 671 (0.18)	24 741 (0.21)	14 278 (0.21)
2006	19 812 (0.17)	11 373 (0.17)	19 757 (0.17)	11 169 (0.16)
2007	14 951 (0.13)	9895 (0.14)	15 307 (0.13)	8769 (0.13)
2008	11 955 (0.10)	9094 (0.13)	12 704 (0.11)	7258 (0.11)
2009	10 082 (0.08)	8029 (0.12)	11 234 (0.09)	6366 (0.09)
2010	5373 (0.05)	4743 (0.07)	6121 (0.05)	3578 (0.05)
Education				
Lower secondary	39 162 (0.33)	17 005 (0.25)	35 319 (0.30)	19 753 (0.29)
Upper secondary	52 977 (0.44)	24 137 (0.35)	48 767 (0.41)	28 885 (0.42)
College	23 393 (0.20)	23 754 (0.35)	28 851 (0.24)	17 392 (0.25)
University	3831 (0.03)	3671 (0.05)	5483 (0.05)	2763 (0.04)
Industry				
Agriculture/forestry	1406 (0.01)	106 (0.00)	963 (0.01)	720 (0.01)
Commercial services	7015 (0.06)	1811 (0.03)	5633 (0.05)	3381 (0.05)
Construction	12 357 (0.10)	2763 (0.04)	9571 (0.08)	4785 (0.07)
Education	3959 (0.03)	9624 (0.14)	9594 (0.08)	4941 (0.07)
Scientific service work	5475 (0.05)	853 (0.01)	4006 (0.03)	2120 (0.03)
Electricity supply	387 (0.00)	317 (0.00)	473 (0.00)	289 (0.00)
Entertainment	1502 (0.01)	379 (0.01)	1203 (0.01)	944 (0.01)
Financial	1701 (0.01)	1189 (0.02)	1923 (0.02)	1282 (0.02)
Health and social work	16 658 (0.14)	27 779 (0.41)	25 274 (0.21)	15 954 (0.23)
Hotel and restaurant	3873 (0.03)	856 (0.01)	2994 (0.03)	1543 (0.02)
Information/communication	5087 (0.04)	1432 (0.02)	4126 (0.03)	2228 (0.03)
Manufacturing	14 306 (0.12)	7560 (0.11)	13 694 (0.11)	7429 (0.11)
Mining/quarrying	2584 (0.02)	1075 (0.02)	2331 (0.02)	1394 (0.02)
Other service	2166 (0.02)	554 (0.01)	1731 (0.01)	1007 (0.01)
Public administration	3765 (0.03)	5528 (0.08)	6850 (0.06)	3756 (0.05)
Real estate	1116 (0.01)	90 (0.00)	768 (0.01)	493 (0.01)
Transport and storage	10 150 (0.09)	3292 (0.05)	8687 (0.07)	4952 (0.07)
Unknown or private households	91 (0.00)	5 (0.00)	61 (0.00)	50 (0.00)
Water supply	982 (0.01)	222 (0.00)	772 (0.01)	560 (0.01)
Wholesale and retail	24 783 (0.21)	3132 (0.05)	17 763 (0.15)	10 964 (0.16)
Company size				
1–9	31 575 (0.26)	3233 (0.05)	22 050 (0.18)	12 281 (0.18)
10–49	48 126 (0.40)	20 514 (0.30)	43 030 (0.36)	24 979 (0.36)

Continued

Table 1 Continued

	No IA, n (%)	IA, n (%)	No IA (IPTW) n (%)	IA (IPTW) n (%)
50–249	12 555 (0.11)	19 437 (0.28)	20 198 (0.17)	11 599 (0.17)
≥250	27 107 (0.23)	25 383 (0.37)	33 142 (0.28)	19 934 (0.29)
Region				
East	55 898 (0.47)	29 625 (0.43)	55 702 (0.47)	31 407 (0.46)
Middle	10 695 (0.09)	6577 (0.10)	10 405 (0.09)	6180 (0.09)
North	14 471 (0.12)	7700 (0.11)	14 002 (0.12)	8849 (0.13)
South	9459 (0.08)	6399 (0.09)	9773 (0.08)	5692 (0.08)
West	28 840 (0.24)	18 266 (0.27)	28 538 (0.24)	16 665 (0.24)
Diagnosis				
Musculoskeletal	43 419 (0.36)	21 570 (0.31)	40 752 (0.34)	24 199 (0.35)
Other types	53 417 (0.45)	34 490 (0.50)	55 200 (0.46)	32 385 (0.47)
Psychological	22 527 (0.19)	12 507 (0.18)	22 467 (0.19)	12 209 (0.18)

in full-time). Furthermore, there was a clear reduction in non-employment of about 2 pp after 1 year for men with IA at the time the initial SA started.

Workers with musculoskeletal illnesses as cause for their initial SA, reached peak effect of IA on RTW after 27 days, where the probability was 3.7 pp (2.4 to 5.0) higher than without IA. This effect magnitude was relatively stable until around day 100, from where it declined and then fluctuated around 2 pp to the end of follow-up. The effect on work was mostly offset by reduced probability of SA, though a slight increase for graded SA was seen and a 2 pp lower probability of non-employment after 1 year.

In the group with psychological diagnoses, the effect on RTW reached a maximum after 37 days, with 5.6 pp (3.5 to 7.7) higher probability with IA. Compared with other subgroups, effects varied much more over time. From the

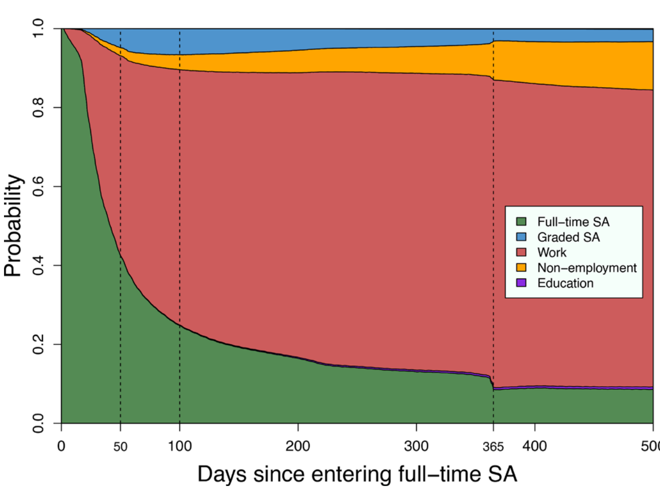

Figure 2 Stacked probability plot of estimated unadjusted state probabilities, for the full study population (both intervention groups, n=187 930), after first initial entry into full-time sickness absence (SA). Individuals may have repeated spells of each state during follow-up, and the plot shows the probability of being in either of the states at all days during the follow-up period.

maximum effect of 5.6 pp, it dropped down to a 3 pp after 1 month, before increasing to over 5 pp 3 months later. The effect then varied between 3 and 5 pp before dropping down to 2 pp after 1 year. In the first year, the effect on RTW was mostly offset by reduced full-time SA, but a small increase in graded SA and reduction in non-employment were seen. One year after an initial SA episode due to psychological illnesses, the probability of non-employment was more than 2 pp lower with IA.

Average effects of IA versus no IA for subgroups are summarised in table 2 in terms of ELOS over the first year. For women, we found that IA led to on average 5.8 (95% CI 2.2 to 9.4) fewer days in full-time SA and 6.0 (95% CI 1.6 to 10.4) more days in work. ELOS in other states were not affected. In men, effects were larger. Men with IA could expect 9.4 (95% CI 5.5 to 13.3) fewer days in full-time SA and 11.2 (95% CI 6.4 to 16.1) more days in work. There was a small increase in ELOS for graded SA of 1.4 days (95% CI −0.4 to 3.2), but the CI included zero. Non-employment was lowered by 3.1 days (95% CI −5.8 to −0.5). For individuals with initial SA due to musculoskeletal illnesses, IA led to on average 8.3 (95% CI 3.7 to 12.9) fewer days in full-time SA and 8.9 (95% CI 3.3 to 14.5) more days in work. ELOS differences for graded SA and non-employment were small, and both confidence intervals included zero. Individuals with psychological diagnoses had the largest differences in ELOS. IA led to on average 14.1 (95% CI 6.0 to 22.3) more days in work over the first year and 11.1 (95% CI 4.2 to 18.0) fewer days of full-time SA. Non-employment was reduced by 3.7 days for the psychological diagnosis group, but the CI included zero.

Sensitivity analyses

To study the impact of covariate adjustment and to investigate robustness of our results, we conducted a series of sensitivity analyses, as described earlier. The analyses supported our main findings, but also indicated effect differences between industries. In the sensitivity analysis

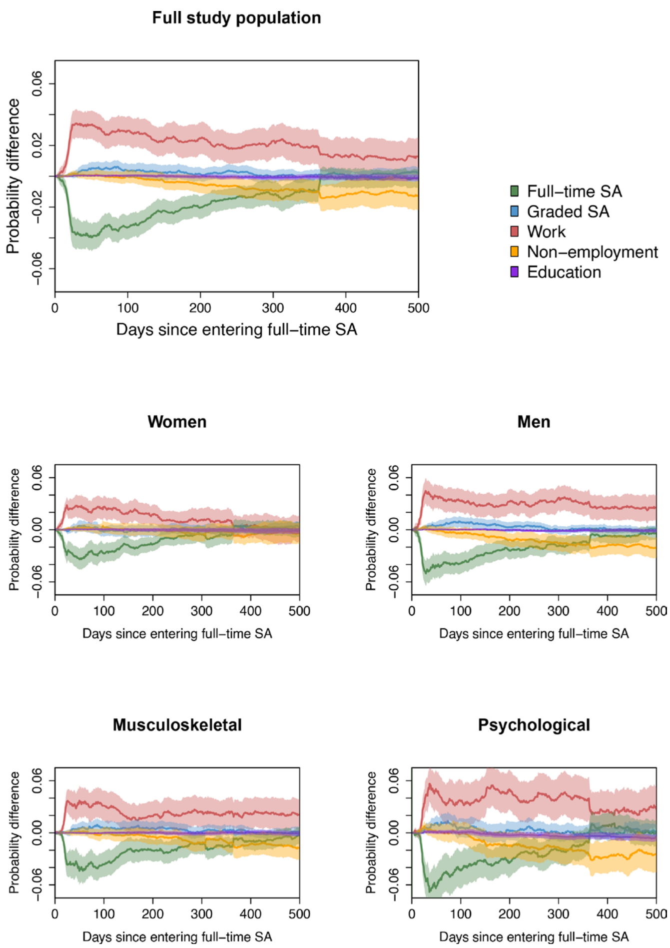

Figure 3 Difference in estimated state probabilities, $\pi^1(t)-\pi^0(t)$, for 500 days following initial entry into full-time sickness absence (SA), where superscript 1 denotes having the inclusive working life agreement (IA) group and superscript 0 denotes not having IA. Estimates were adjusted for confounding using inverse probability of treatment (IPT) weighting. Faded areas are 95% CI based on 1000 bootstrap samples. The topmost plot in the figure shows results for the entire study population. The middle two plots are for women and men separately, and the bottom two are separated between musculoskeletal and psychological diagnoses pertaining to the initial SA spell.

of the woman in the study population, where all diagnoses related to pregnancy, childbearing and family planning were removed, we found a somewhat higher effect of IA than in the analysis which included all the women. Detailed results from these analyses are described in online supplemental sections S.2–S.6 and shown in online supplemental figures 1–5.

The sequence plots that illustrate individuals' multistate histories (see online supplemental figure 6) showed that the most common history was one with a short period of full-time SA, less than 2 months, followed by uninterrupted stay in the work state. We have provided more details on the sequence plots in online supplemental section S.7.

A barplot that shows gender representation in the largest industries is included in online supplemental figure 7 and further described in online supplemental section S.8. Here we found that men worked mostly within construction, manufacturing and transport and women worked in education and health industries.

DISCUSSION

We found that having access to the Norwegian IA Agreement, which included measures for preventing and reducing SA, at the time of initiating a first long-term SA episode, increased the probability of later work and decreased the probability of later full-time SA during the first 500 days after first entering SA. The probability of later non-employment was also reduced, particularly after 1 year. Larger effects were found for men than for women, and among individuals with musculoskeletal or psychological diagnoses connected to the initial SA spell. For women, the effect of IA was negligible after 1 year, while for men, the effect remained also after the first year.

A reduction in full-time SA and a slight increase in graded SA are in accordance with the first IA goal of reducing SA. In addition, it is worth noticing that non-employment 1 year after entering SA, appears to be reduced in workplaces with IA, especially for men. From a health perspective, the underlying intention of IA is to reduce SA by remaining in work, also after the first year when the right to certain SA benefits in Norway ceases. Our results show that having IA contributes to reducing SA by keeping people in work, rather than by existing work. Furthermore, while previous studies found that IA enterprises may have higher SA, or that IA has none or minor effects on the occurrence of SA,[8 11 12] our study shows that once on SA, IA contributed towards reducing the number of SA days. This could indicate that IA had a larger effect on SA duration than on the occurrence of SA.

A recent paper on the effect of IA on SA prevalence and duration, using similar data sources but other methods, found a beneficial effect of IA in terms of reduced duration for both musculoskeletal and psychological diagnoses, particularly in men.[12] Another study, from 2020, on IA and risk of long-term SA spells found small differences, but a slight decrease for female workers in stratified analyses.[11] Effects of IA are greater among individuals who had musculoskeletal or psychological diagnoses, compared with other diagnoses, is expected, as the intervention is specifically aimed at these patient groups.[6]

We estimated effects of having access to IA and did not investigate which IA measures had most effect or whether workers had accessed them. There is supporting evidence that various workplace health-promotion interventions may prolong working life in certain types of work.[25] A Cochrane review from 2015 found moderate evidence for workplace interventions being effective in increasing RTW in workers on sick leave with musculoskeletal disorders (first and lasting RTW) and mental health problems (only first RTW).[26] A systematic review from 2018[27] further supports these findings. However, a review of studies on

Table 2 Expected length of stay (ELOS) in days, for 1 year after entering long-term full-time sickness absence (SA) from work, with 95% CI, based on 1000 bootstrap samples

	IA	No IA	Difference
Full study population			
Full-time SA	88.8 (87.2 to 90.5)	96.4 (95.3 to 97.5)	−7.6 (−10.3 to −4.8)*
Graded SA	18.1 (17.2 to 19)	17.3 (16.7 to 17.9)	0.8 (−0.7 to 2.2)
Work	240.8 (238.7 to 242.8)	232.4 (230.9 to 233.8)	8.4 (4.9 to 11.9)*
Non-employment	16.2 (15.1 to 17.3)	17.8 (17.1 to 18.5)	−1.6 (−3.4 to 0.2)
Education	0.9 (0.7 to 1.1)	1.0 (0.8 to 1.1)	−0.1 (−0.5 to 0.3)
Women			
Full-time SA	94.2 (92.3 to 96.1)	100.0 (98.3 to 101.7)	−5.8 (−9.4 to −2.2)*
Graded SA	21.9 (20.7 to 23.2)	21.9 (21.1 to 22.8)	0.0 (−2.1 to 2.1)
Work	232.3 (230.0 to 234.6)	226.3 (224.2 to 228.4)	6.0 (1.6 to 10.4)*
Non-employment	15.3 (14.0 to 16.6)	15.5 (14.4 to 16.5)	−0.2 (−2.5 to 2.1)
Education	1.2 (0.8 to 1.6)	1.2 (1.0 to 1.5)	0.0 (−0.6 to 0.6)
Men			
Full-time SA	82.9 (80.3 to 85.5)	92.3 (91.0 to 93.6)	−9.4 (−13.3 to −5.5)*
Graded SA	13.4 (12.2 to 14.7)	12.0 (11.4 to 12.6)	1.4 (−0.4 to 3.2)
Work	250.3 (247.2 to 253.5)	239.1 (237.4 to 240.8)	11.2 (6.4 to 16.1)*
Non-employment	17.5 (15.6 to 19.3)	20.6 (19.8 to 21.4)	−3.1 (−5.8 to −0.5)*
Education	0.6 (0.3 to 0.8)	0.7 (0.6 to 0.9)	−0.1 (−0.6 to 0.3)
Musculoskeletal			
Full-time SA	92.0 (89.2 to 94.8)	100.3 (98.4 to 102.1)	−8.3 (−12.9 to −3.7)*
Graded SA	20.2 (18.7 to 21.8)	18.7 (17.9–19.6)	1.5 (−1.0 to 3.9)
Work	236.0 (232.4 to 239.6)	227.5 (225.2 to 229.8)	8.5 (2.6 to 14.4)*
Non-employment	16.1 (14.3 to 17.8)	17.7 (16.7 to 18.6)	−1.6 (-4.3 to 1.1)
Education	0.7 (0.4 to 1.1)	0.8 (0.5 to 1)	0.0 (−0.6 to 0.5)
Psychological			
Full-time SA	104.3 (100.1 to 108.6)	115.4 (112.7 to 118.1)	−11.1 (−18.0 to −4.2)*
Graded SA	22.4 (20.2 to 24.5)	21.2 (19.9 to 22.5)	1.2 (−2.2 to 4.6)
Work	213.0 (207.9 to 218.1)	198.9 (195.9 to 201.9)	14.1 (6.0 to 22.3)*
Non-employment	23.9 (20.7 to 27.1)	27.7 (26.0 to 29.3)	−3.7 (−8.6 to 1.2)
Education	1.1 (0.6 to 1.7)	1.7 (1.3 to 2.2)	−0.6 (−1.6 to 0.4)

*The last column shows the difference in ELOS between IA and no IA, where an asterisk indicates CIs of the difference that do not include zero.
IA, Agreement for a More Inclusive Working Life.

the effect of interventions for improving RTW in workers with common mental illness found that the available interventions did not lead to improved RTW rates.[28] One should also note, as IA has been gradually introduced at a national level in Norway over the study period and beyond, that it is likely that IA has had an impact on SA and RTW at a societal level. This effect is not picked up in our study, as we consider individual differences of having IA or not over the study period.

A strength of this study is the use of a large cohort with high completeness, with detailed information on individual longitudinal work participation and a large set of confounders. Another strength is the use of multistate modelling. We believe that the study serves as a good example of how longitudinal data from multiple registries can be used to construct detailed outcome trajectories and that IPT weighted multistate models offer a suitable way of estimating effects on such outcomes. The approach allows us to analyse more detailed long-term work-related outcomes than traditional approaches, and to calculate various relevant outcome measures, ELOS being one example. However, there are also various limitations. Most importantly, this is an observational study, and access to the measures given through IA was not randomised, but subject to the decision of the company signing up for IA. Even though adjustment for various assumed confounding variables was made, there is no guarantee that residual confounding is not present. However, sensitivity analyses were not able to detect residual confounding in settings where more detailed confounder information was available. The negative control by analysing pre-exposure multistate histories indicated the same. Note that if the negative control had showed different pre-exposure histories, even after initial confounder adjustment, these histories could also be adjusted for as additional baseline information.

Given the assumptions of no unmeasured confounding, positivity and consistency, the IPT weighted multistate model aims to mimic the scenario one would see if access to IA was randomised at baseline (time of first long-term SA episode). Note also that we implicitly assume that IA exposure acts as if given at first SA. As our analyses are restricted to individuals without any recent SA history, we believe this to be a reasonable assumption. The mechanisms through which IA potentially promotes faster RTW are many. One can assume that some are connected to individual measures undertaken at IA workplaces, while others are related to measures available for IA workplaces in general.

There were notable differences in the estimated effects of IA for women and men, which can have various explanations. The Norwegian labour market has a high level of gender segregation,[29 30] which can also be observed in our study population. For our study sample, a high proportion of men worked in construction, manufacturing and transport, while women dominated the educational and healthcare industries. Although the available measures are the same for every IA company, it is reasonable to expect that the implementation and effect of IA measures vary substantially across workplaces, occupations and industries. The governmental appointed Research Group for the IA Agreement writes in their report from 2018[31] that there are substantial differences between industries and types of work regarding challenges with SA and SA reducing measures. Also, as observed in most western countries over many years,[32–34] women generally have a higher prevalence of SA than men. The gender differences in labour outcomes are the subject of extensive research and debate. Some studies have indicated that differences in work-related outcomes can be caused by unfavourable working conditions among women,[35 36] while others find less favourable conditions among men.[33] Some studies suggest women handle work-related strain worse than men.[37] There are also results indicating that the double burden of household work affects women to a higher degree than men,[38] and if the SA comes as a result of challenges at home, measures focusing on the workplace might not be as effective. A qualitative study of interventions and rehabilitation activities in connection with RTW from 2021[39] found that women expressed a need for home-related interventions, whereas men expressed a need for organisational interventions to counter feelings of resignation at work. As the IA Agreement is focused on workplace-related measures, it may therefore be the case that the IA measures better target men. Furthermore, a substantial part of the initial SA cases among women in our study population was in connection with pregnancy, childbearing and family planning, and IA measures may not be as relevant for SA tied to such diagnoses. Online supplemental analysis showed that when excluding these cases, the effects of IA among the remaining women were somewhat higher.

The IA Agreement is specific to Norway, and it is not likely that similar effects would have been seen in other countries. Norway is known for having a generous welfare system and high protection for individual workers. In addition, the cohort studied was young (28–43 years), and results do not necessarily generalise to older populations. Future work should focus on studying specific measures for preventing and reducing SA and how they vary with different types of work, industries, diagnosis types and other worker characteristics.

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An initiative for a more inclusive working life and its effect on return-to-work after sickness absence – a multi-state longitudinal cohort study

Supplementary Material

S.1 Estimands and statistical methods

A multi-state model can be seen as a stochastic process $\{X(t) \mid t \geq 0\}$, taking values from a set of possible states $S = \{1, 2, 3, ..., S\}$ [1, 2, 3]. In the present study, S = 6, and t was days since inclusion. The model is governed by transition intensities $\alpha_{jk}(t)$, referring to the probability of a jump to state k from state j within a small time interval Δt, divided by Δt, as Δt approaches 0:

$$\alpha_{jk}(t) = \lim_{\Delta t \to 0} \frac{\Pr(X(t+\Delta t) = k \mid X(t-) = j)}{\Delta t}$$

for all j,k in S, where $j \neq k$.

When $\boldsymbol{A}(t)$ is the matrix of cumulative transition intensities with elements $A_{jk}(t) = \int_0^t \alpha_{jk}(s)\, ds$, for $j \neq k$ and $A_{jj}(t) = -\sum_{j\neq k} A_{jk}(t)$, the state probabilities $\boldsymbol{\pi}$(t) with elements $\pi_j(t) = \Pr(X(t) = j)$ are found using the Aalen-Johansen estimator [4], by

$$\hat{\boldsymbol{\pi}}(t) = \boldsymbol{\pi}(0) \prod_{(0,t]} (\mathbf{I} + \Delta \boldsymbol{A}(u)) \tag{1}$$

where $\boldsymbol{\pi}(0)$ is the initial state distribution at time zero. In settings with time-to-event data, right censoring and no covariates, the elements of $\boldsymbol{A}$(t) can be estimated using the Nelson-Aalen estimator [4]. State probabilities (also known as state occupational probabilities) are a simple and intuitive quantities for multi-state outcomes and can be seen as an extension of regular survival probabilities (e.g., from Kaplan-Meier curves).

To assess the effect of the Norwegian Inclusive Working Life Agreement (IA), and the within measures for preventing and reducing SA, we sought to identify the average treatment effect (ATE), as the difference in state probabilities

$$\theta(t) = \pi_j^1(t) - \pi_j^0(t) \tag{2}$$

for all $j \in S$, where $\boldsymbol{\pi}^a$(t) are the counterfactual state probabilities if everyone in the study population was fixed to IA status a (taking the values 1 and 0 for IA and non-IA respectively).

From the state probabilities we calculated

$$\theta = \int_0^{365} \pi_j^1(t)\, dt - \int_0^{365} \pi_j^0(t)\, dt \tag{3}$$

representing the difference in expected length of stay (ELOS) in state j, over the first year, for the situations where everyone was fixed to $a = 1$ and $a = 0$.

Hoff R, *et al. BMJ Open* 2022; 12:e062558. doi: 10.1136/bmjopen-2022-062558

The estimands in formula (2) and (3) can be identified under conditional exchangeability (no unmeasured confounding), positivity and consistency [5]. Adjustment for confounding was made by applying baseline inverse probability of treatment (IPT) weights [5], also known as propensity score weights, while fitting hazard models for every possible transition in the model.

More precisely, we fitted a weighted additive hazards regression model [4] on the form

$$\alpha_{jk}(t\,|a) = \beta_{jk0}(t) + \boldsymbol{\beta}_{jk}^{T}(\mathrm{t})a$$

for all possible transitions *jk*, where $\boldsymbol{\beta}^{\mathrm{T}}$ (t) are time-varying regression functions and $\beta_{jk0}(t)$ is the baseline j → k transition intensity. For each observation we applied the baseline inverse probability of treatment (IPT) weight $\widehat{w}_i$, for the corresponding individual *i*. Estimates $\widehat{\boldsymbol{B}}_{jk}(t)$of the cumulative regression functions

$$\boldsymbol{B}_{jk}(t) = \left[\int_0^t \beta_{jk0}(u)du\,, \int_0^t \beta_{jk}^T(u)du\right]^T$$

are found using least squares techniques [4]. For the two possible values of a, we then found the cumulative transition intensity matrices by

$$\hat{A}_{jk}^{a}(t) = \hat{A}_{jk}(t|a) = \widehat{\boldsymbol{B}}_{jk}^{T}(t)\boldsymbol{a}^{*}$$

where $\boldsymbol{a}^{*} = (1, a)^T$, which again was plugged into the formula in (1), and thus identify the estimands in formula (2) and (3).

To calculate the IPT weights $\widehat{w}_i$, we modelled IA status A, given baseline confounders **Z** in a logistic regression model

$$logit\,\mathrm{Pr}(A|\,\mathbf{Z}) = \beta^T\mathbf{Z}$$

Using this model, for each individual *i*, the conditional probability of having their assigned IA status a_i given their covariate values z_i at baseline, $\mathrm{Pr}(a_i \mid \boldsymbol{z}_i)$ were estimated and used to calculate the (stabilized) IPT weight [5]

$$\widehat{w}_i = \frac{\mathrm{Pr}\,(a_i)}{\mathrm{Pr}(a_i\,|\boldsymbol{z}_i)}$$

where $\mathrm{Pr}(a_i)$ is the sample proportion with IA status equal to a_i at baseline.

S.2 Sensitivity analysis 1: Using subsets of adjustment variables

As a first sensitivity analysis, we compared the results from the main analysis with results from a series of analyses adjusting for all possible subsets of the main adjustment set, including the empty set – in total 256 models. Results are shown in Supplementary Figure 1.

In the left panel of Supplementary Figure 1, the unadjusted differences in state probabilities are seen to be almost twice as big as after confounder adjustment using IPT weighting. While in the right panel, we see how including smaller and less complete sets of confounders can lead to shifts in both directions compared to the main model.

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S.3 Sensitivity analysis 2: Adjusting for additional covariates measured for men during military

Most of the men included in the study underwent military conscript examinations at the age of 18. Here they measured, among other things, IQ score, BMI, physical stamina score and a rough assessment of military eligibility (physical and mental). These data were available to us from the Norwegian Armed Forces Personnel Data Base. As these variables were not measured for all the individuals in the cohort, especially women, they were not adjusted for in the primary analyses. However, as a sensitivity analysis, we compared weighed analysis for men not taking and taking these variables into account. The results are shown in the left panel in Supplementary Figure 2. The plot shows no visible differences. In fact, the absolute differences in effect estimates came after the third – fourth decimal. We also tried adding conscript variables in an alternative analysis where the variables for education and workplace industry from the main analysis were left out. Here we were able to detect visible differences in effect estimates from the plot. Results of this analysis are shown in the right panel of Supplementary Figure 2.

S.4 Sensitivity analysis 3: Pre IA (1997-1999) multi-state histories as a negative control

Individual multi-state histories are also available for individuals in the cohort before IA was introduced and can be utilised as a negative outcome control [6]. The question of interest is then whether these earlier multi-state histories differed between those with later IA and those without, and if the IPT weights used sufficiently adjusted for such a difference. We therefore considered state histories during the period from 1st of January 1997 to 31st of December 1999, where we compared both the crude difference in state probabilities for the same intervention groups as in the main analysis, and a weighted analysis using the IPT weights of the main analysis. The results are found in Supplementary Figure 3. Results showed that the later IA groups differed between 1997 and 2000 in terms of education probability (IA group about 4 percentage points more likely to be in education) and work probability (non-IA group about 3 percentage points more likely to be in work). For non-employment there were only small differences. The probabilities for full-time or graded SA did not differ much, as one would expect due to the restriction of no history of SA one year before inclusion. However, after applying the IPT weights from the main analysis, also the differences in work histories that were there disappeared. This indicates that the confounding adjustment through these weights sufficiently covered differences in earlier work life (all states) histories.

S.5 Sensitivity analysis 4: Analysis of a limited selection of industries

From the information in Table 2 in the main article, it appeared that a large proportion of IA companies were in industries where public workplaces are typically overrepresented, such as education and health services. Information on public vs private workplace was not available for the study. In this section, we performed a separate analysis for a limited selection of industries, assumed to have many private workplaces, namely wholesale and retail, construction, manufacturing, commercial services and transport and storage. Results from these analyses are found in Supplementary Figure 4. We found a higher effect of IA within this subgroup, more akin to the effect seen in men in the main article.

S.6 Sensitivity analysis 5: Analysis with initial SA spells related to pregnancy, childbearing and family planning removed

Since our study population were in an age span 28-42, a high proportion of the initial SA cases were related to pregnancy, childbearing and family planning. We removed 20355 cases with such diagnosis types and ran the analysis for the remaining women. The results can be seen in Supplementary Figure 5. As can be seen in the Figure, there were an increased effect of IA among the remaining women after these diagnoses were removed.

Roughly one month after inclusion, we found that by removing these cases, the effect of IA on work was increased in the range of 0.4-0,6 pp higher probability of work, while being offset by similar reduction for being in SA. The effect difference is noticeable smaller and almost non-existent 100 days into the study and this pattern is seen for a good hundred days going forward. Towards the end of the study, we again see some increase in the effect on work in this limited stratum, but now the increased effect on work is offset by an even greater reduction in non-employment than seen in the full female population.

S.7 Sequence analysis of state trajectories within different industries

To illustrate how typical patterns of individual state trajectories differ between different industries and IA status, we made so-called sequence plots using the TraMineR package in R. Different industries with similar characteristics were grouped together. In order to plot individual trajectories with some form of clarity, we based the plots on 500 randomly sampled individuals within each stratum. The sequence plots are displayed in Supplementary Figure 6. Here, the state histories are sorted backwards after similar states, and indications of some differences in common patterns between the industries can be seen.

In all industries, the by far most common type of individual state history is that consisting of a shorter period of full-time SA, typically less than 2 months, followed by an uninterrupted stay in the work state. Furthermore, the increased amount of work seen in the IA intervention group, seems to come from individuals who are not in work at the final observation day, but rather have varying length of work periods in the middle of the observation time span. Partial SA appears to be less frequently used within construction and manufacturing industries.

S.8 Barplot showing number of individuals in the six biggest industries

The barplot in Supplementary Figure 7 illustrates the segregated labour market, where women typically work within health and education, while men are overrepresented in construction, manufacturing and transport industries.

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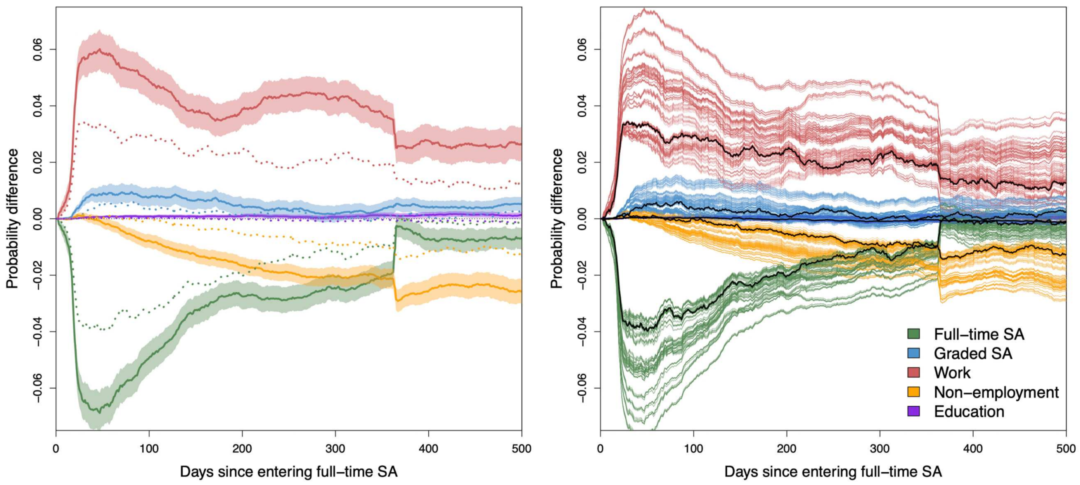
Tables

Supplementary Table 1 Total number of transitions made by the study population of n = 187 930 individuals, over 90 231 405 person days, during individual follow-up of up to 500 days after entering full-time sickness absence (SA).

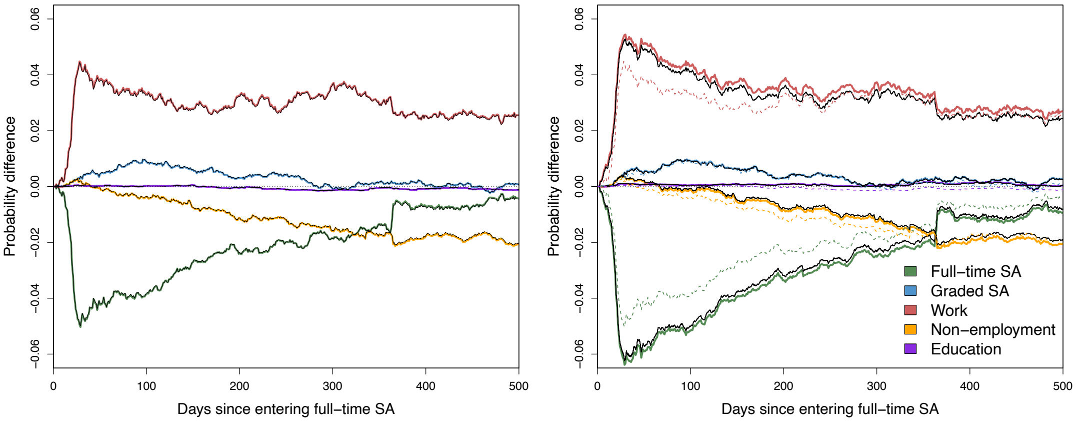
FROM \ TO	Full-time SA	Work	Graded SA	Non-employment	Education	Death
Full-time SA	0	197 774	32939	18760	492	163
Work	64 888	0	18562	37074	2003	78
Graded SA	9127	35254	0	1853	49	0
Non-employment	5902	28468	750	0	1015	34
Education	131	1526	31	737	0	0
Death	0	0	0	0	0	0

Figures

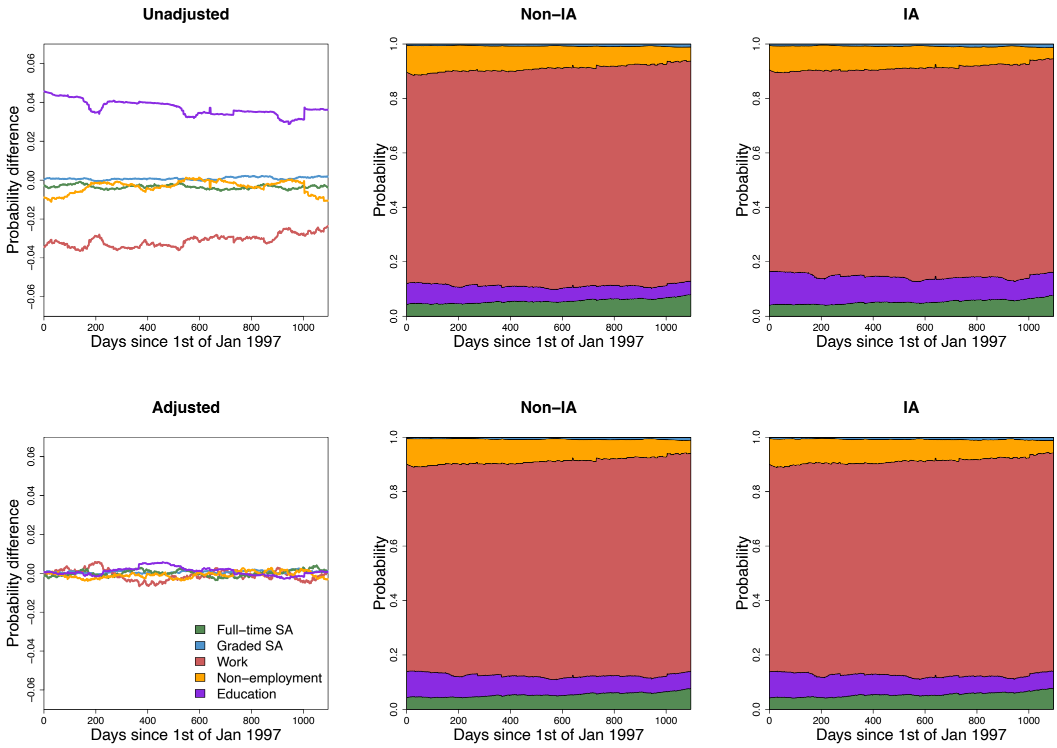


Supplementary Figure 1: Differences in estimated state probabilities, $\hat{\boldsymbol{\pi}}^1(t) - \hat{\boldsymbol{\pi}}^0(t)$, for the full study population, after entering long-term full-time sickness absence (SA), where superscript 1 denotes having the Inclusive Working Life Agreement (IA) and superscript 0 denotes not having IA. Faded areas are 95 % confidence intervals based on 1000 bootstrap samples. **Left:** The full-drawn lines are unadjusted estimates, while the dotted lines show the inverse probability of treatment (IPT) weighted estimates from the main article. **Right:** The black lines illustrate the IPT weighted estimates from the primary analysis in the main paper and colored lines are IPT weighted estimates from using different subsets of the main adjustment set when constructing the weights.

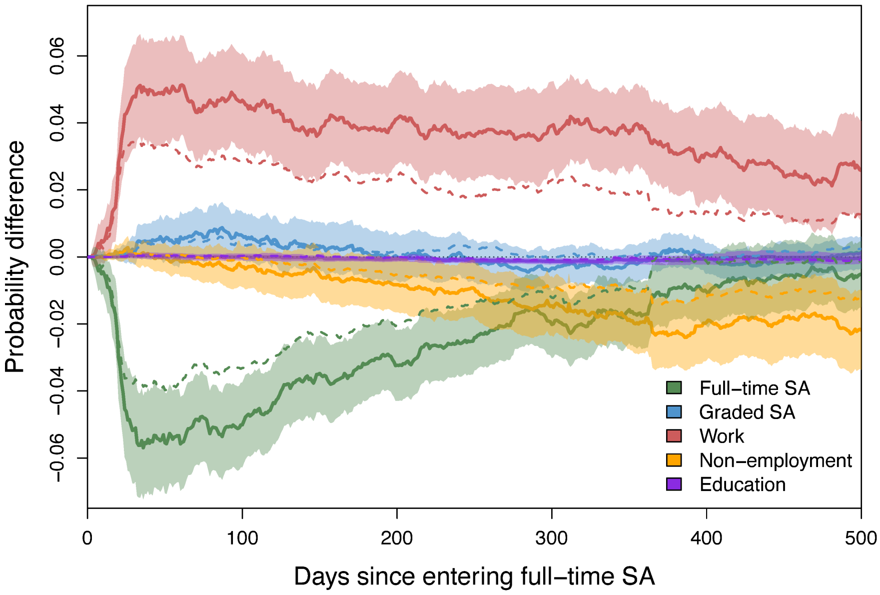
Hoff R, *et al. BMJ Open* 2022; 12:e062558. doi: 10.1136/bmjopen-2022-062558



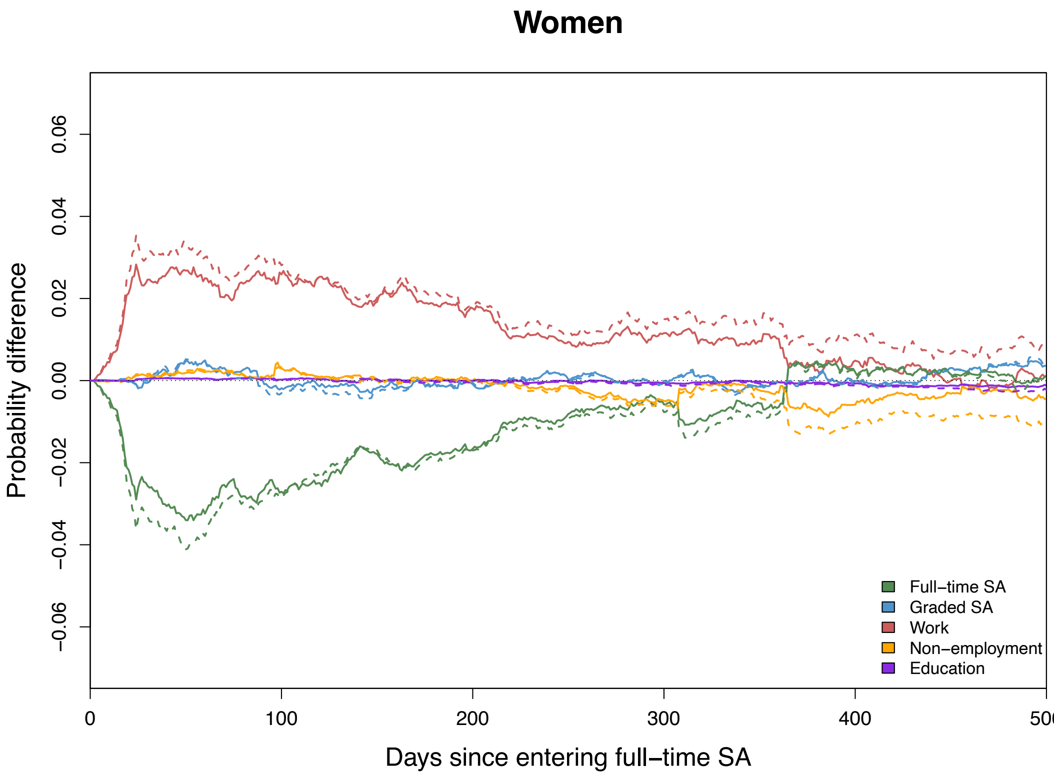
Supplementary Figure 2: Difference in estimated state probabilities, $\hat{\boldsymbol{\pi}}^1(t) - \hat{\boldsymbol{\pi}}^0(t)$, for men who completed military conscript examinations, after entering long-term full-time sickness absence (SA), where superscript 1 denotes having the Inclusive Working Life Agreement (IA) and superscript 0 denotes not having IA. **Left:** The colored lines are estimates adjusted for confounding by inverse probability of treatment (IPT) weighting using the main confounder set. Black lines show the estimates from when conscript variables IQ score, BMI, physical stamina test and military eligibility test were also adjusted for. **Right:** The black lines show estimates where also conscript variables IQ score, BMI, physical stamina test and military eligibility test were adjusted for but leaving out the covariates for education and workplace industry. Full drawn colored lines are estimates adjusted for confounding by IPT weighting, leaving out education and workplace industry from the confounder set. Dotted colored lines are original estimates adjusted for confounding using the full main adjustment set.



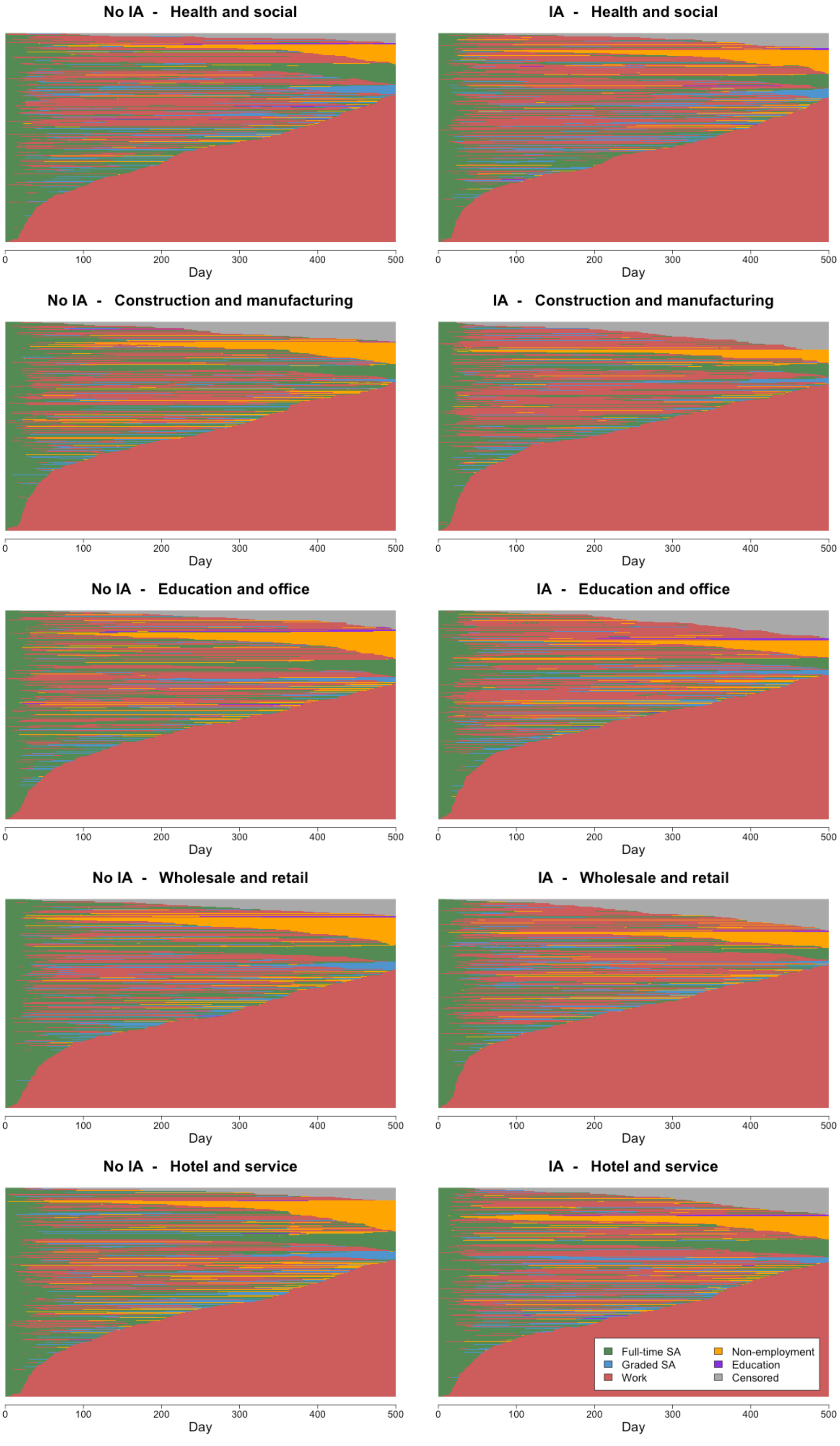
Supplementary Figure 3: The left column shows differences in state probabilities, $\hat{\boldsymbol{\pi}}^1(t) - \hat{\boldsymbol{\pi}}^0(t)$, where superscript 1 denotes having the Inclusive Working Life Agreement (IA) and superscript 0 denotes no IA. The middle and right column show state occupation probabilities for no IA and IA respectively. The top row shows unadjusted estimates, while the bottom row shows estimates adjusted for confounding using inverse probability of treatment (IPT) weighting.



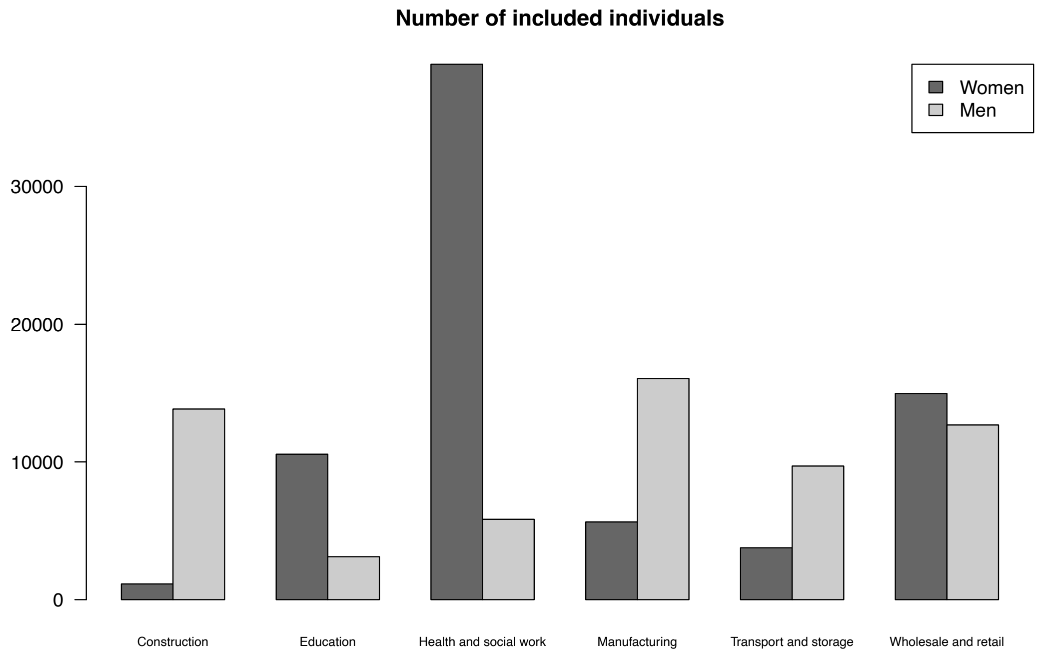
Supplementary Figure 4: Difference in estimated state probabilities, $\hat{\boldsymbol{\pi}}^1(\mathrm{t}) - \hat{\boldsymbol{\pi}}^0(\mathrm{t})$, after entering long-term full-time sickness absence (SA), where superscript 1 denotes having the Inclusive Working Life Agreement (IA) and superscript 0 denotes not having IA. Estimates are adjusted for confounding using inverse probability of treatment (IPT) weighting. Faded areas are 95 % confidence intervals based on 1000 bootstrap samples. Full-drawn lines are estimates for the limited selection of industries, wholesale and retail, construction, manufacturing, commercial services and transport and storage, while the stippled lines show the estimates from the primary analysis (all industries).



Supplementary Figure 5: Difference in estimated state probabilities, $\hat{\boldsymbol{\pi}}^1(t) - \hat{\boldsymbol{\pi}}^0(t)$, after entering long-term full-time sickness absence (SA), where superscript 1 denotes having the Inclusive Working Life Agreement (IA) and superscript 0 denotes not having IA. Estimates are adjusted for confounding using inverse probability of treatment (IPT) weighting. Faded areas are 95 % confidence intervals based on 1000 bootstrap samples. Full-drawn lines are estimates for all the women in the study population, while the stippled lines show updated estimates after removing the 20,355 women with initial SA diagnosis related to pregnancy, childbearing and family planning.



Supplementary Figure 6: State histories for 500 randomly sampled individuals within each group of industry. The sequences are ordered bottom up based the state occupied on the last observation day (day 500) and backwards on this state order: work, partial sick-leave, full-time sick-leave, non-employment, death, education and censoring.



Supplementary Figure 7: Number of included individuals working in the six most represented industries of the study population.

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