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ORIGINAL RESEARCH ARTICLE

Productivity Loss Across Socioeconomic Groups Among Patients With Low Back Pain or Osteoarthritis: Estimates Using the Friction-Cost Approach in Norway

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Abstract

Objectives Our aim was to estimate the productivity loss (PL) among patients with low back pain (LBP) or osteoarthritis (OA) across socioeconomic groups, using the friction-cost approach (FCA).

Methods A total of 175,550 patients aged 18–65 years were included at their first diagnosis in specialty care between 2011 and 2016. PL was calculated for the year following diagnosis using individual wages, while adjusting for the friction length at 78 days per episode, a team production multiplier at 1.6, compensation mechanisms of 26.8%, and a chain-of-vacancies multiplier at 3.95. We included a simpler FCA model, omitting the latter three parameters, and a human capital approach (HCA) model. Socioeconomic stratifications were created based on education and income. One-way sensitivity analysis was used to assess the influence of the parameters in the full FCA model.

Results The overall mean number of absent days was 23, while it was 25.3 and 20.1 for those with low and high education levels. The per-patient friction costs were €4395 among all patients and when extending the friction length to 98 days costs were €4342. For those with low and high education levels, the costs were €3671 and €4464, respectively. The costs in the simple FCA and HCA models were €1539 and €2088.

Discussion Socioeconomic status and model design are sources of variation in PL. In health economic applications with PL and in patient populations with large socioeconomic differences, adjusting for these factors may be as important as sensitivities in parameters such as the friction length.

1 Introduction

Socioeconomic status and its effect on health and labour force participation constitutes an area of great interest to policymakers and researchers [1]. The association between a higher frequency of work absence and lower socioeconomic status (e.g. education and/or income) has been established in previous studies across countries, time and settings [2–9]. These differences in work absence would be reflected in the economic costs affiliated with work absence across socioeconomic groups. Economic costs in health economic evaluations are usually calculated by estimating the loss in economic output (i.e. productivity loss) using either the human capital approach (HCA) or the friction cost approach (FCA) [10]. Both methods take the societal perspective on costs, but differ in their estimation methods. The HCA focuses on the individual and calculates the potential production loss for the specific individual and the FCA also focuses on the individual, but incorporates the employer perspective as well to calculate the individual-level production loss until the production of the individual is replaced via another worker [11]. The FCA typically yield lower productivity loss estimates than the HCA, but the ratio depends heavily on specific settings (e.g. time perspective, included cost items, and disease) in each study [12].

In cost-of-illness and cost-effectiveness studies, the FCA has been applied to a lesser degree than the HCA [12, 13]. One reason for this may be the operational ease of implementing the HCA, as the information needed is the number of days absent from work and the monetary valuation of those days (e.g. wages). The same parameters are included in the FCA, but losses accrue for a shorter time during the friction period, which is the period it takes an employer to replace the absent worker.

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Key Points for Decision Makers

Socioeconomic differences in work absence are reflected in the productivity losses; such stratifications are important to highlight the heterogeneity in productivity losses.

This study estimates the productivity loss across different socioeconomic groups using the friction cost approach and administrative data on work absence and socioeconomics among patients with low back pain and osteoarthritis in Norway, which has not been examined in prior studies.

Productivity losses across socioeconomic differences in health economic applications provide decision makers with important sources of information for making informed decisions with finite resources.

When considering the employer perspective in the FCA, it is important to account for the dynamics that occur in the workplace when a worker is absent. Additional model parameters have been suggested for this purpose, such as compensation mechanisms [14, 15], team production multipliers [16, 17] and vacancy multipliers [18–20]. The compensation mechanism parameter accounts for the net production loss caused by a sick employee, which may be compensated for by others at the workplace or by an absent employee after returning to work. A team production multiplier effect can also occur if the absent worker is part of a broader team and absence causes the entire team's production to decrease. The vacancy multiplier parameter accounts for situations in which an absent worker is replaced by an employed worker instead of an unemployed worker, resulting in a new vacancy in the old workplace and potentially causing a chain of vacancies. Failure to include these parameters may result in productivity losses that are unaccounted for. However, deriving proper data and methods for these parameters has been a challenge, which may be a factor contributing to the limited use of the FCA compared with the HCA. Most applications of the FCA and comparisons with the HCA have been carried out without including the parameters described above.

Methodological contributions in recent years have made progress in deriving the parameters described above, particularly the friction length itself, resulting in FCA being easier to implement and more applicable across geographies and settings. Two recent papers published by Hanly and his co-authors have made important contributions by establishing easy-to-follow methods to calculate the friction length and vacancy multiplier in different settings [19, 21]. The contribution of the vacancy multiplier is particularly important, as it was a source of major criticism against the FCA in the early years after its development [18]. Methods to calculate the compensation mechanism and team production multiplier have been previously applied using patient and employee surveys [14, 16, 17]. These parameters essentially depend on individual-level characteristics. Accounting for these parameters in FCA analyses can produce better and more relevant FCA estimates than the original application which did not include these parameters [22].

While the aforementioned methodological contributions can be included in FCA analyses, we also know that work absence patterns differ by socioeconomic groups resulting in observable differences in productivity losses across socioeconomic groups. Awareness of productivity loss differences by socioeconomic groups can be important as there are multiple examples in which socioeconomic status may matter, such as the possibility of cost effectiveness only in some socioeconomic subgroups [23–25], treatment provision and treatment adherence [26–29], and clinical treatment effects [30, 31]. Therefore, heterogeneous productivity losses can serve as an important source of information in policy considerations and health-economic applications such as cost-effectiveness analyses.

An accurate calculation of productivity losses across socioeconomic groups depends principally on the accurate summarisation of the number of days absent from work and the identification of socioeconomic status among the study population in question. The most reliable and unbiased data sources on work absence and socioeconomic status are large nationwide administrative databases with universal coverage and linkage possibilities, such as the high-quality registers in the Nordic countries. Such data sources are highly valuable as most studies on the FCA rely on self-reported survey and questionnaire data on work absence [13], which is subject to recall bias [32] and more often than not, small samples.

One of the major underlying causes of work absence such as sick leave and disabilities is musculoskeletal diseases, which are estimated to account for 14% of total societal costs across disease categories (in the top three together with cancer and psychiatric/mental disorders) [33]. Low back pain and osteoarthritis are among the most common musculoskeletal diseases associated with a high rate of absence from work.

There have been no prior studies simultaneously applying the model parameters described earlier, that is, the recently developed methods of the FCA, to a patient population with musculoskeletal disease in combination with high-quality nationwide administrative data on work absence, income, and education level.

This study aimed to estimate productivity loss using the FCA and HCA across different socioeconomic groups with administrative data on work absence and socioeconomics, among patients with low back pain (LBP) and osteoarthritis (OA) in Norway.

2 Methods

2.1 Study Design

This was a nationwide observational study using administrative registers on work absence and socioeconomics in Norway combined with aggregated data to define model parameters (compensation mechanism, team production multiplier, and vacancy multiplier). The study population consisted of Norwegian patients with a primary diagnosis of LBP (ICD-10 codes: M48.0, M51, M53.2–9, M53.8–9, M54.0–1, M54.3–6, M54.8–9, and M96.1) or OA (ICD-10 codes: M15–19) between 2011 and 2016 in Norwegian inpatient or outpatient hospital care (specialty care). The index date was set as the date of the first diagnosis. Patients outside the working age range (18–65 years) at the time of index or who were diagnosed between 2008 and 2010 were excluded, as we wanted to study working-age patients beginning from their first recorded diagnosis. The follow-up period was 1 year following index.

All individual-level data sources (the National Patient Register for identification of patients, the sick leave and disability register [FD-Trygd] from Statistics Norway for work absence, and socioeconomic registers on income and education from Statistics Norway) were linked using personal identifiers available in the registers. These data sources and the linkage process are described in greater detail elsewhere [34] and in the electronic supplementary material (ESM). Ethical approval was obtained from the regional ethical review board in South-East Norway (reference number: 28745).

2.2 Patient Characteristics and Socioeconomic Status

Patient characteristics at the time of diagnosis are presented. Age and sex were recorded at the index date, including whether the patient was included based on an LBP diagnosis, OA diagnosis, or both. The number of net sick leave and disability pension days in the year following diagnosis, average annual gross pre-tax wage income in the three calendar years before the index, employment status (whether a patient had wage income) and highest attained educational level in the calendar year prior to index were collected from Statistics Norway.

All patient characteristics were stratified by socioeconomic status and were defined according to education and income. Educational stratification was defined according to the highest achieved educational level (below upper secondary school, upper secondary school and above upper secondary school) in the year of diagnosis. Income stratification was based on wage income and categorised by quantiles as no or low income ($<$ Q25), middle income (Q25–Q75) and high income ($>$ Q75).

2.3 Productivity Loss Using the Friction Cost Approach

Friction costs were calculated for the year following the diagnosis date. Sick leave and disability leave episodes (collectively written as work absence episodes) that started at or after the diagnosis date were included to capture episodes that were assumed to be related to LBP or OA. Work absence episodes included information on start and end dates for each episode (defined as one continuous period of absence; if an individual was absent for 3 weeks, worked for 2 days and then was absent for another 3 weeks, that would be defined as two episodes) and the extent of the leave (proportion of absence compared with full-time employment). Sick leave episodes of <14 days were not included in the register data collection. The recorded absence episodes were part of administrative data, and were not self-reported. See the ESM for a more detailed description of the register.

We applied and reported the total number of net work absence days, calculated as the length of each episode multiplied by the recorded extent of leave of each episode (e.g. 10 calendar days of work absence with 50% extent of leave is 5 net days). The friction period was applied to the number of net absent days in each episode, not over the full year, as patients may have had multiple episodes during the year. Episodes starting earlier than 1 year after follow-up and ending after that point were included up to the date marking 1 year after diagnosis.

Productivity losses were calculated using three models: a main FCA model, a simple FCA model without additional model parameters, and an HCA model. One-way sensitivity analysis and probabilistic sensitivity analysis were conducted on the main FCA model. All costs in this study are expressed in Euros as of 2021.

2.3.1 Model Description

The productivity loss for a single episode in all models was calculated using Eq. 1 with varying restrictions imposed on the parameters in the different models.

$$\text{Productivityloss}_{\text{ie}} = w_i \cdot A_{\text{ie}} \cdot (j - c) \cdot v \tag{1}$$

Parameter w is the monetary valuation of each absent day for each employee i, as is standard in previous studies; it is the marginal productivity proxied by the daily wage rate. A

is the number of net absent days in each separate absence episode e, with the restriction in Eq. 2.

$$A_{ie} = \begin{cases} \text{Days absent} & \text{if net days absent} \leq \text{friction length} \\ \text{Friction length} & \text{if net days absent} > \text{friction length} \end{cases} \tag{2}$$

The model parameters j, c, and v represent the team production multiplier, compensation mechanism, and vacancy multiplier, respectively. The vacancy multiplier is only applied to absence episodes beyond the friction length as a potential vacancy only occurs when a worker is replaced, that is, at the end of the friction length, and is represented by the restriction in Eq. 3.

$$v = \begin{cases} 1 & \text{if net days absent} \leq \text{friction length} \\ 3.95 & \text{if net days absent} > \text{friction length} \end{cases} \tag{3}$$

In the main FCA model, j, c, and v were set to 1.6, 0.268, and 3.95, respectively, and in the simple FCA and HCA models, they were set to 1, 0, and 1 (the term $(j–c)\cdot v$ was 1; removing the parameters impact on the results). The friction length in both FCA models was empirically calculated as 78 days for Norway during our study period (2011–2016) following the methodology and formula applied by Hanly et al., including the commonly applied period of 28 days of training for the new employee [21]. No restrictions were placed on A in the HCA model; thus, the costs were calculated for all net absent days. The daily wage rate (w) in all models was the daily wage of the average individual wage income of the 3 calendar years prior to index. In the sensitivity analysis, we used the wage for the full study population (€92.2). A patient could have multiple work absence episodes during the study period and for each patient we summed the productivity losses for all absence episodes. The final productivity loss estimate is the sum of all productivity losses divided by the entire study population. The individual-level parameters were wages and the number of net absent days in each absence episode, while the other model parameters were based on aggregated characteristics; thus the term $(j–c)\bullet v$ is equal for all individuals. Table 1 presents an overview of the model parameters, their values, and the sourcing used in each model.

To illustrate the calculation of productivity loss in the main FCA model, if one work absence episode for one patient lasted for 25 net days, the productivity loss would be as follows: 92.2·25·(1.6–0.268) ·3.95 = €12,127. If a work absence episode lasted beyond the friction length, A was set to 78 and the productivity loss would be €37,837.

The term $w\cdot A\cdot(j–c)$ represents the internal productivity loss from the perspective of the initial employer with an absent worker, which is multiplied by the vacancy multiplier representing the losses among other employers if the number of days exceeds the friction length. It is assumed that the values of the compensation mechanism and the team production multiplier are equal for all employers throughout the vacancy chain. As productivity losses are estimated only for work absence episodes, lower job-productivity is not included (presenteeism); thus our estimates only focus on productivity losses due to absenteeism.

In the ESM, a more detailed description and sourcing of all parameters are provided, with a script to derive all model parameters, including the friction length and vacancy multiplier from publicly available Eurostat databases.

2.3.2 One-Way and Probabilistic Sensitivity Analysis

In the one-way sensitivity analysis, the model parameters in Eq. 1 (j, c, and v) were decreased or increased 25% one by one with the main FCA model for all patients as the reference case (Table 1). Costs by socioeconomic subgroups and different wage rates were added as part of the one-way sensitivity analysis to compare such impacts to the other model parameters.

Probabilistic sensitivity analysis (PSA) was performed to simultaneously capture adjustments in the model parameters. The model parameters were sampled from truncated normal distributions with mean and standard deviation as the mean value used in the main FCA model and standard deviation at 25% of the mean value (Table 1). A truncated normal distribution was chosen because there is no established literature on the underlying distribution for these parameters, and truncation was applied because the model parameters have natural limits (e.g. the friction length cannot be negative). For computational simplicity in the PSA, no correlations were assumed between the model parameters; despite unemployment occurring in both the estimation of the friction length and the vacancy multiplier. The wage rate was the same as in the main models, as wage defines the worth of one absent day and is not associated with uncertainty per se. The number of absent days was also kept at an individual level, as recorded in the administrative data, similar to the other models, and was not associated with uncertainty. The sampled model parameters were applied equally to all individuals. PSA was run 10,000 times and performed separately for the socioeconomic subgroups.

2.4 Statistical Analysis

Categorical variables are presented as frequency and proportion, and continuous variables are presented as mean, median, and standard deviation. The significance level was set at 5% to calculate the confidence intervals. All data management and analyses were performed using RStudio [37].

Table 1 Overview of model parameters depending on analysis perspective

	Main FCA	Simple FCA	HCA	One-way analysis	Probabilistic analysis
Days absent	Net days absent as recorded in the data				
Daily wage rate *Statistics Norway wage statistics* [35]	Individual wage	Individual wage	Individual wage	Education-specific mean wages: <*Upper secondary school:* €64.9 *Upper secondary school:* €90.6 >*Upper secondary school:* €115.1 Mean wage rate of the individual wages (€92.2)	Individual wage
Friction length *Eurostat labour market statistics* [36]	78 days	78 days	n/a	± 25% (58–98 days)	Sampled from a truncated normal distribution with parameters mean, SD, min, and max at 78, 20, 0, and 365 days, respectively
Team production multiplier *Nicholson et al.* [16]	1.6	1	1	± 25% (1.2–2)	Sampled from a truncated normal distribution with parameters mean, SD, and min at 1.6, 0.4, and 1, respectively. No maximum was applied
Compensation mechanism *Knies et al.* [15]	0.268	0	0	± 25% change (0.201–0.335)	Sampled from a truncated normal distribution with parameters mean, SD, min, and max at 0.268, 0.067, 0, and 1, respectively
Vacancy multiplier *Eurostat labour market statistics* [36]	3.95	1	1	± 25% change (2.96–4.94)	Sampled from a truncated normal distribution with parameters mean, SD, and min at 3.95, 0.98, and 1, respectively. No maximum was applied

FCA friction cost approach, *HCA* human capital approach, *SD* standard deviation

3 Results

3.1 Patient Characteristics

The total number of patients identified with a diagnosis of LBP or OA in specialty care was 550,216. After all inclusion criteria were met, 175,550 were included in the study (see Fig. S1 in the ESM for a flow chart of patient numbers).

The mean age at diagnosis was 46.6 years, and 49.9% were male (see Table 2 for all patient characteristics by subgroup); the mean age and proportion of males were higher in the groups with high education or income. Disposable income and employment were higher in the subgroup with the highest educational level than among those with less education. Educational levels were lower in the lower-income group than in the higher-income group. LBP was more common in the lower socioeconomic groups than in the higher socioeconomic groups. Some patients did not have education (n = 3372) or income (n = 4668) information registered and were not included in the respective subgroups.

In the year following the diagnosis, the mean number of work absence days with sick leave or disability across all patients was 20.2 and 3.1, respectively (Table 2). Among the educational level groups, those with the lowest education had the highest number of work absence days, while those in the middle-income group had the highest work absence among the income groups. Work absence due to disability pension was more common in the lower socioeconomic groups than the higher socioeconomic groups.

Table 2 Patient characteristics

Outcome	All patients	<Upper secondary school	Upper secondary school	>Upper secondary school	No or low income	Middle income	High income
Number of patients	175,550	39,772 (22.7%)	74,214 (42.3%)	58,192 (33.1%)	51,047 (29.1%)	79,872 (45.5%)	39,936 (22.7%)
Age at diagnosis[a]	46.6 (11.8) [48.1]	44.5 (12.4) [46.7]	47.5 (11.8) [49.3]	46.9 (11.2) [47.8]	42.6 (13.7) [43.8]	47.7 (10.8) [48.8]	50.2 (9.1) [51.1]
Males[b]	87,512 (49.9%)	20,963 (52.7%)	39,757 (53.6%)	24,703 (42.5%)	21,709 (42.5%)	34,382 (43%)	28,457 (71.3%)
Wage income (in € 000s)[a]	33.4 (25.7) [33.5]	23.4 (19.4) [23.9]	33 (21.1) [33.5]	42 (31.4) [40.5]	8.7 (8) [7.2]	35.3 (6.2) [35.4]	65.3 (28.6) [56.9]
Employed[b]	151,155 (86.1%)	30,553 (76.8%)	65,347 (88.1%)	53,373 (91.7%)	32,152 (63%)	76,999 (96.4%)	39,241 (98.3%)
Highest educational level[b]							
<Upper secondary school	39,772 (22.7%)	39,772 (100%)			18,415 (36.1%)	16,358 (20.5%)	3,949 (9.9%)
Upper secondary school	74,214 (42.3%)		74,214 (100%)		20,066 (39.3%)	38,293 (47.9%)	14,878 (37.3%)
>Upper secondary school	58,192 (33.1%)			58,192 (100%)	11,673 (22.9%)	24,386 (30.5%)	20,904 (52.3%)
Sick leave days[a]	20.2 (48.6) [0]	20.3 (52.3) [0]	21.7 (50.5) [0]	18.5 (43) [0]	14.8 (46.2) [0]	23.9 (51.5) [0]	20 (44.1) [0]
Disability days[a]	3.1 (25.3) [0]	5 (32.8) [0]	3.2 (25.7) [0]	1.7 (18.4) [0]	7.6 (40.3) [0]	1.5 (16.9) [0]	0.6 (10.8) [0]
Sick leave and disability days[a]	23.3 (53.7) [0]	25.3 (60.1) [0]	24.9 (55.4) [0]	20.1 (46.1) [0]	22.5 (59.6) [0]	25.4 (53.6) [0]	20.6 (45.2) [0]
Diagnosis type[b]							
OA	67,194 (38.3%)	12,834 (32.3%)	30,101 (40.6%)	23,384 (40.2%)	16,161 (31.7%)	31,782 (39.8%)	18,142 (45.4%)
LBP	94,988 (54.1%)	23,687 (59.6%)	38,033 (51.2%)	30,920 (53.1%)	31,090 (60.9%)	41,518 (52.0%)	19,016 (47.6%)
Both	13,368 (7.6%)	3251 (8.2%)	6080 (8.2%)	3888 (6.7%)	3796 (7.4%)	6572 (8.2%)	2778 (7.0%)

LBP low back pain, *OA* osteoarthritis, *SD* standard deviation

[a]Continuous variable, presented with mean (SD) [median]

[b]Categorical/binary variable, presented with n (%)

In Fig. 1, the vertical axis shows the proportion of patients with a specific number of net work absence days over the year following diagnosis. In the subgroup ‘Upper secondary school’, 32% of patients had at least one absent day and 8% had 100 days or more. The proportion of work absence was lower in the lower socioeconomic groups than in the higher socioeconomic groups. Thus, while the average number of work absence days was higher in the lower socioeconomic groups, the proportion of patients with work absences was higher in the higher socioeconomic groups. The variation among income groups was greater than among educational groups.

3.2 Productivity Loss

In the main FCA model, the friction cost during the year following diagnosis was €4395 per patient (Table 3). In the simple FCA model, with the parameters for multiplier effects due to team production, chain of vacancies, and compensation mechanisms set at 1, 1, and 0, respectively, the friction cost was €1539. Therefore, the inclusion of additional model parameters increased the simple friction cost estimate by 185.5%. Using the HCA model, the mean cost was €2088, thus the HCA yielded 35.7% higher costs than the simple FCA model and 47.5% higher costs than the main FCA model. For the HCA, the costs directly reflect the number of days absent, which the FCA analyses do not show, as the friction length caps the number of days over which productivity loss is calculated.

The friction cost estimates were lower in the group with less than upper secondary school education than in the group with more than upper secondary school education; however, friction costs were higher in the group with only upper secondary school education. In the main FCA model, friction costs ranged from 28.2 to 165.4% for the model including all patients across the different socioeconomic groups (Table 3). The costs for the simple FCA model ranged from 8.4 to 62.6% of those in main FCA model including all patients, and the HCA model costs ranged from 13.5 to 80.3%.

Fig. 1 The proportion of patients with a specific (or higher) number of work absence days according to socioeconomic group. The figure does not include the proportion with 0 work absence days for visual clarity

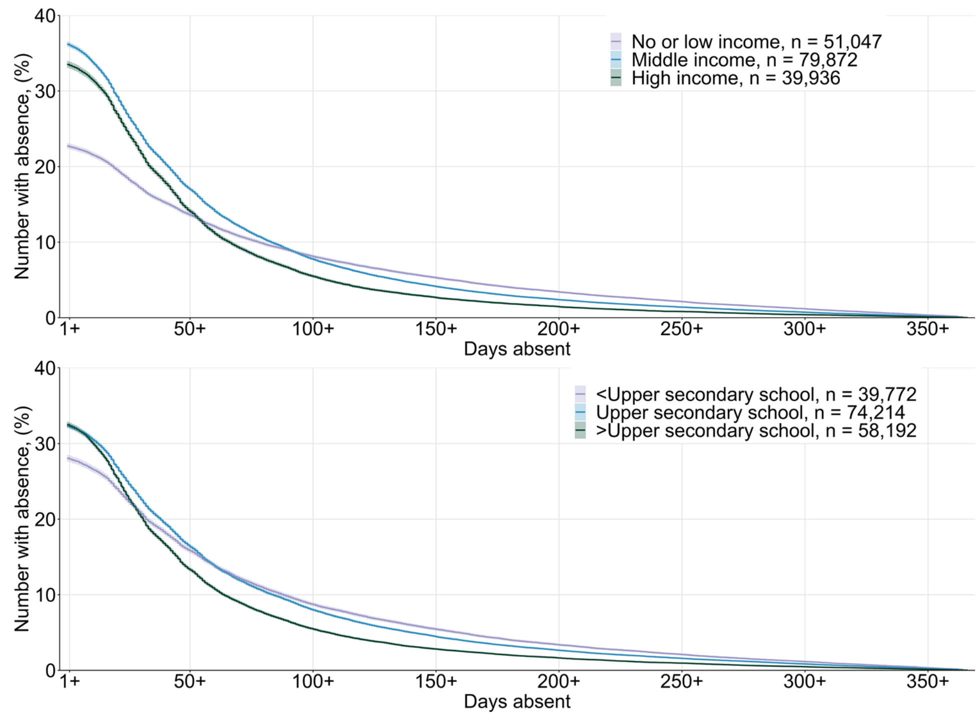

Table 3 Average per-patient productivity losses

Group	Main FCA model mean (95% CI) [SD] share of 'All patients' main FCA	Simple FCA model	HCA model
All patients	4395 (4335–4456) [12,818], 100.0%	1539 (1524–1555) [3367], 35.0%	2088 (2062–2114) [5485], 47.5%
< Upper secondary school	3671 (3563–3779) [10,988], 83.5%	1175 (1148–1203) [2765], 26.7%	1742 (1694–1790) [4876], 39.6%
Upper secondary school	4730 (4635–4825) [13,183], 107.6%	1615 (1591–1640) [3379], 36.7%	2239 (2198–2279) [5628], 50.9%
> Upper secondary school	4464 (4355–4574) [13,472], 101.6%	1744 (1713–1774) [3735], 39.7%	2199 (2153–2246) [5757], 50.0%
No or low income	1239 (1201–1278) [4392], 28.2%	370 (361–379) [1068], 8.4%	592 (575–610) [2043], 13.5%
Middle income	5135 (5050–5219) [12,073], 116.8%	1772 (1751–1793) [3014], 40.3%	2447 (2411–2483) [5189], 55.7%
High income	7270 (7079–7460) [19,346], 165.4%	2750 (2699–2800) [5157], 62.6%	3528 (3448–3609) [8207], 80.3%

All costs are expressed in Euros

CI confidence interval, *FCA* friction cost approach, *HCA* human capital approach, *SD* standard deviation

For all models, the variation in costs among the education groups was smaller than that among income groups. This is expected because individual wages were used both as the valuation of days absent and to define the subgroups, and it is also illustrated in the smaller variation in income among the educational groups compared with the income groups (Table 2).

3.3 One-Way Sensitivity Analysis

In the one-way sensitivity analysis (Fig. 2), costs were compared with the main FCA model for all patients (€4395). Among the parameters, the team production multiplier has the largest impact on productivity loss, followed by the vacancy multiplier, compensation mechanism, and friction length. Note that a higher compensation mechanism would lead to lower costs, as more production is compensated. The impact of a change in the parameters on the costs is symmetric (as they are multiplicative constants), except for the friction length. Extending the friction length to 98 days increases the friction costs to €4342 but also reduces the number of absence episodes activating the vacancy multiplier and vice versa. Therefore, the impact of changing the friction length (in either direction) on friction costs is relatively small compared with changing the other model parameters.

The use of different wage rates has a small impact on productivity loss estimates. In one case, the average wage

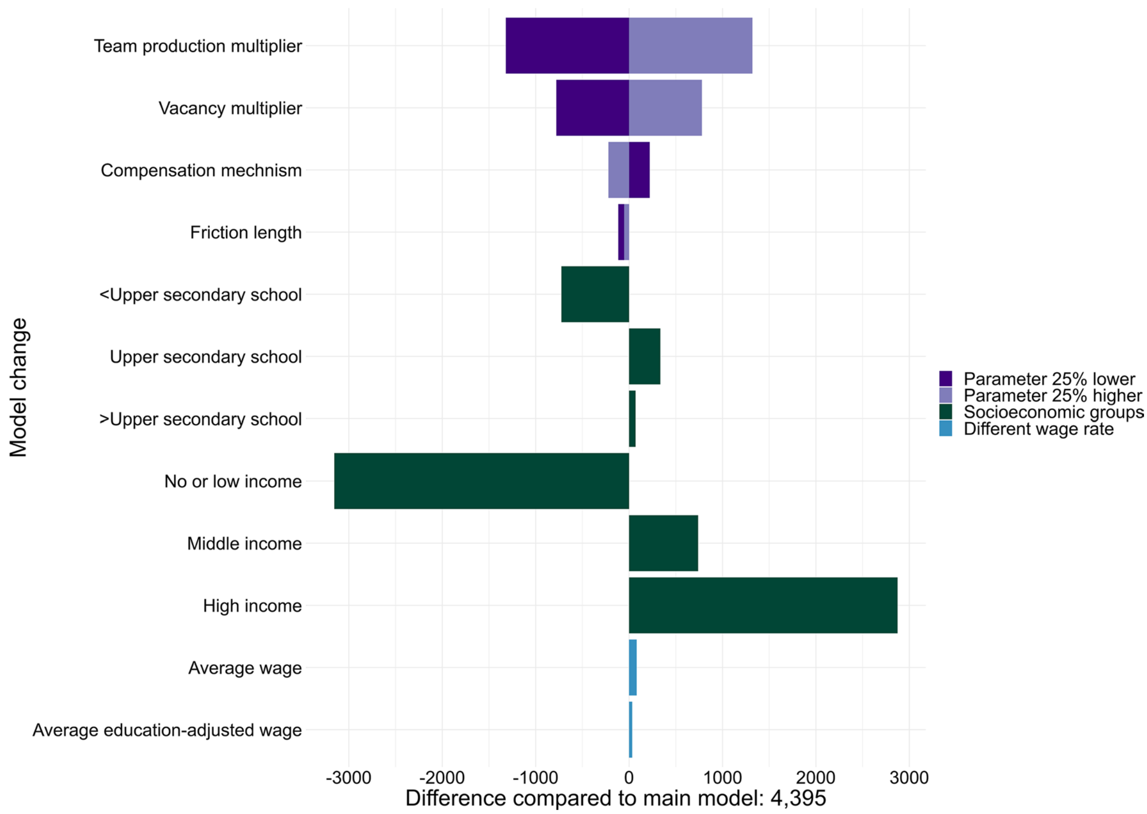

Fig. 2 One-way sensitivity analysis. The bars for the socioeconomic groups are found by subtracting the extended model costs for that group from the extended model cost of all patients, e.g., cost for higher than upper secondary school was €12,256 yielding a difference of €800 as indicated by the graph

in the study population was applied to all individuals, and in another case, the average wage by the education group was applied to all individuals with that level of education. Both scenarios yield relatively similar estimates, as in the case of using individual wages directly.

Compared with stratifying the main model cost by socioeconomic group (Table 3), a change in the friction length or compensation mechanism yields similar variations in costs when adjusting for educational status, while changes in team production and vacancy multipliers are greater. Stratifying by income group yielded larger differences in the main model than adjusting the model parameters.

3.4 Probabilistic Sensitivity Analysis

In the PSA (Fig. 3), where all model parameters were simultaneously varied and sampled, the distributions of mean productivity losses for all patients and socioeconomic subgroups were relatively bell-shaped. For all patients, the mean PSA estimate was €3976, that is, between the main and simple FCA model costs, and ranged between €1177 and €6728 across the socioeconomic groups. Overall, 33.8% of the PSA estimates were higher than the main FCA model costs.

4 Discussion

This was the first study to calculate productivity loss using the FCA among patients with LBP and OA and simultaneously apply the recent developments in FCA methods in the same study. Productivity losses ranged from €370 to € 7270 per patient, depending on the model specification and socioeconomic group. Cost variations depend on the value of the model parameters, wage rates, and the difference in the number of absent days among socioeconomic groups. We also found that the main model FCA costs exceeded the HCA costs and that income group differences were greater than education group differences. The large variation in costs highlights the importance of accurate high-quality data and assumptions regarding cost parameters.

We were largely able to produce similar results on the difference in sick leave and disability pension by socioeconomic groups found in other settings [2–6]. These differences were also reflected in the different productivity losses

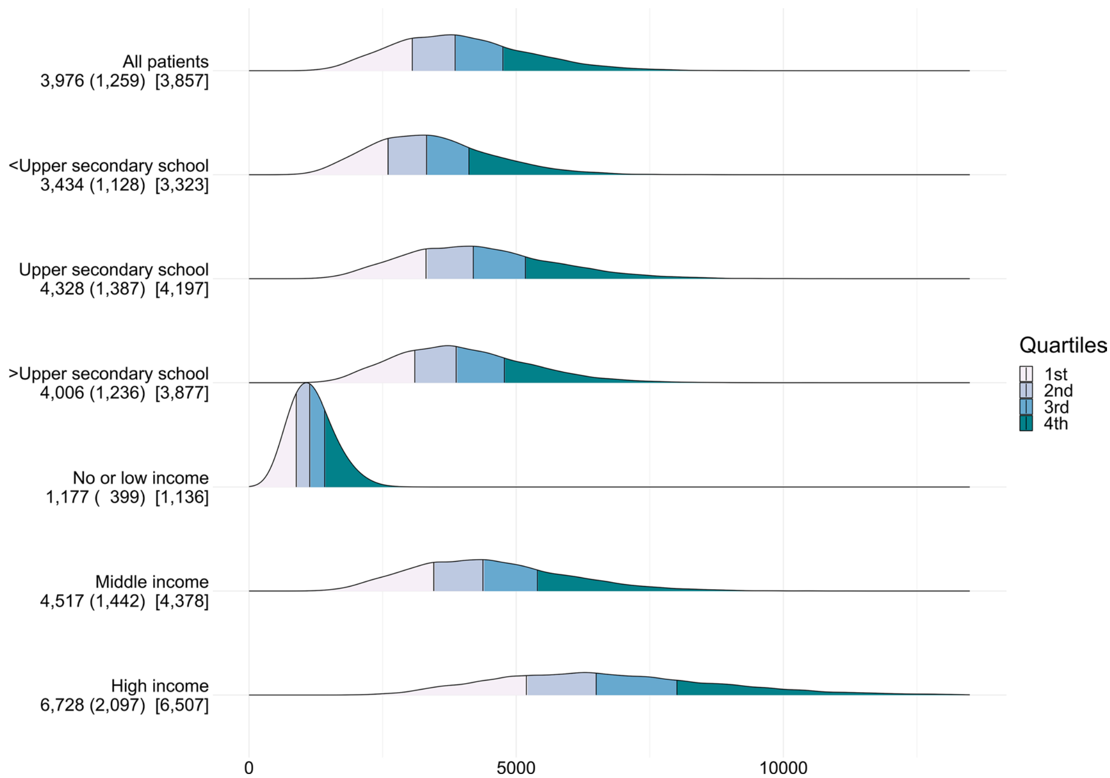

Fig. 3 Probabilistic sensitivity analysis with the density distribution of the mean probabilistic sensitivity analysis estimates in Euros. The numbers below each group are the mean, standard deviation, and median of the associated distribution

across the socioeconomic groups. In the higher socioeconomic groups, the proportion with work absence was higher than that in the lower socioeconomic groups, although the average length of work absences was shorter. Absences using sick leave were relatively more common than absences with disability pension in the higher socioeconomic groups compared with the lower socioeconomic groups. Higher rates of disability pension among those with low education/income compared with those with high education/income are in line with previous studies [7–9]. Wages are relatively more important in productivity loss among those with high education or income compared with those with low education or income due to the higher wages in the former groups, while the number of absent days is relatively more important for those with low education or income.

The difference in work absence among the income groups is not entirely surprising, as employment is needed to gain sick pay, and disability pension may be a reason behind a person earning an income and not working. This concurrent relationship is less apparent for the educational groups as patients' education usually is achieved and completed years before they are included in the study population. We interpret the differences in work absence patterns among socioeconomic groups as associations and do not claim that the reported relationships between socioeconomics and work absence are causal effects. However, these relationships may indicate that job type compositions differ across socioeconomic groups, leading to different work absence patterns. For example, individuals with higher education may have less physically demanding jobs than those with lower education, resulting in fewer or shorter periods of sick leave or fewer disabilities. It may also be the case that those with higher education are more aware of disease prevention measures, resulting in fewer illnesses and patients adapting their lifestyles accordingly. For example, in the guidelines for the treatment of OA, arthritis education is an integral and fundamental part of treatment and aims to educate patients on the disease and how to live with OA, and recommends lifestyle changes [38]. If participation in these programmes, the understanding of their content, and adherence to recommendations depends in some way on the socioeconomic background of patients, adaption and implementation of these programmes can be tailored to patients' socioeconomic background, thereby helping reduce socioeconomic disparities.

Although this study does not directly address whether productivity loss should be adopted by decision makers and policy makers, such as health technology assessment (HTA) agencies, it clearly demonstrates the existence of substantial differences in productivity losses across socioeconomic groups. Health economic evaluations should consider socioeconomic differences in productivity losses and conduct stratified analyses on relevant subgroups [39]. Failure to account for socioeconomic differences may result in unintentional neglect of interventions that may be cost effective in one socioeconomic group but not in another. HTA agencies and other decision makers may face the challenge of analysing interventions that are only cost effective for certain subgroups of patients. For example, an intervention may only be cost effective for high-wage earners or based on its effect on the patient population's ability to work. In some cases, decision makers may attempt to reduce the impact of socioeconomic status by applying the same wage rate to all patients regardless of their socioeconomic status, but this approach does not address underlying differences in sick leave and disability patterns among socioeconomic groups. This was also the first study to simultaneously apply the recently developed methods of Hanly et al. [19, 21] to calculate empirically based estimates of the friction length and vacancy multiplier. In the current literature, these parameters, in addition to the compensation mechanism [15] and team production multiplier [16], are derived from aggregated data sources. While relying on aggregated measures is the current best practice for estimating productivity losses, these parameters are fundamentally individual characteristics. The true friction length at a firm depends on the specific characteristics of the absent worker and the workplace. For example, it may be reasonable to believe that the impact of an absent neurosurgeon is greater than that of an absent fast food worker. This study shows that individual-level characteristics are of high importance, and differences among socioeconomic groups were similar to the impact of changes in several of the aggregated model parameters on productivity loss. The economic interpretation of the one-way sensitivity analysis is that team production and internal firm dynamics matter more in calculating productivity losses than friction length and vacancy chains. However, more work is needed to further individualise the aggregated parameter used in this study and to gain a greater understanding of what impacts productivity loss the most. By developing more disaggregated parameters, the FCA would also be able to incorporate more socioeconomic parameters compared with the HCA.

In previous studies, HCA costs have usually been greater than FCA costs [12]; however, the results show that this is not universally true. When estimating costs over a 1-year period accounting for compensation mechanisms, team production, and vacancy chain multipliers, the final cost estimate in the FCA model is higher than that in the HCA model. Both the FCA and HCA have merits depending on the researcher's preferences, perspectives, and goals. If a researcher does not have an explicit preference for the HCA over the FCA, both approaches are worth implementing, particularly as recent methodological contributions have made it easier to implement the FCA [19, 21]. Despite the use of different estimation methods, the estimated costs can overlap. Thus, the conventional view that the HCA may overestimate the costs and the FCA will underestimate the costs may still hold [40, 41] depending on the estimation methods, but not because the cost estimate itself is higher in the HCA than in the FCA. The two FCA models show that costs are heavily dependent on the workplace dynamics (team production and vacancy chain multipliers, compensation mechanisms, and friction length) that occur when a worker is absent, which are included in the model, and the value of these parameters. Given the incorporation of the employer-perspective with the FCA, the aim may be to include as many of these parameters as reasonably possible in FCA calculations. FCA costs may be severely underestimated if this is left unaccounted for, as shown in this study, where the difference between the simple FCA and main FCA models was almost 300%. Considering that previous FCA estimates only included the friction length and may not have included compensation mechanisms, team production multipliers, or vacancy multipliers or may have only included one or two of them, FCA costs may have been underestimated in the previous literature. In our view, the impact of modifying the simple FCA and comparing such estimates to those of the HCA should be explored further in future studies.

LBP and OA are merely two possible chronic pain conditions, and the socioeconomic differences in productivity losses seen here may not be generalisable to other chronic or non-chronic conditions with different patterns of sick leave, disability pension, and socioeconomic composition. Similarly, productivity losses were only evaluated within the first year after diagnosis. With a longer time period, the costs of disability pension would arguably play a larger role, as disability is, by definition, long-term absence. The lower socioeconomic groups in our study had more disability-related long-term absences than did the higher socioeconomic groups. If a longer time perspective was taken, more HCA costs would accumulate after the end of the friction period, and the differences between the HCA and FCA would be larger. The differences across socioeconomic groups would be lower because of the higher long-term disability rates among the lower socioeconomic groups. However, the dynamics between short-term sick leave and long-term disability pensions in relation to socioeconomic status, comparisons using the HCA and FCA, and productivity losses are currently unexplored in this study. Future studies should explore these dynamics, including productivity losses in other patient populations with different sick leave and disability pension patterns.

4.1 Strengths

A strength of this study is the use of high-quality and complete nationwide registers to capture socioeconomic status and the accurate number of work absence days. These databases are subject to a high degree of completeness, have no loss of follow-up (other than death or emigration) and cover the entire population. For the first time, a Norway-specific friction length was applied to a Norwegian setting. An assumed friction length of 3 months is often applied in FCA studies and empirical estimates using stock and flow data on vacancies in the labour market are usually derived from the Netherlands [13, 22, 42].

4.2 Limitations

A limitation of this study is its reliance on aggregated data for the friction length and vacancy multiplier, an assumption regarding the 28-day training period, and the use of survey results in the literature from settings other than Norway for the compensation mechanism and team production multiplier. In particular, there is uncertainty regarding what these values are for the latter parameters that have been derived from a non-Norwegian setting, and the true value may be outside the bounds of the parameter distribution used in the PSA. For computational simplicity, we also assumed that these parameters were equal throughout the vacancy chain. The individual aspects of all parameters were not taken into account, which is a limitation due to their individualistic nature. Future studies could further develop methods and focus on attaining more disaggregated model parameters from the relevant country, disease, job, education, or other group settings. The 28 days included in the friction length as an assumption of the length of the training period is also subject to large individual and job-type differences.

We did not include any estimates on productivity losses due to presenteeism (i.e. reduced on-the-job productivity). Presenteeism costs are estimated to be substantial elsewhere, and our productivity loss estimates are underestimated in general [43].

Owing to data availability and the structure of the data, short-term absences (<14 days) were not recorded in the register. This is a data limitation, but it also means that we miss many work absence episodes and underestimate losses. Given that these absences are shorter than the friction length, their value for estimating productivity would be identical for the HCA and FCA. However, the impact of socioeconomic status could play a role if such short-term absences showed different absence patterns. From our results, we observe that groups with higher education/income have a higher proportion of patients with an absence than those with low education/income. Future studies could investigate whether this also holds for absences shorter than 14 days. If so, productivity losses could be relatively higher for the high education/income groups, potentially reducing the differences across socioeconomic groups.

5 Conclusion

The socioeconomic differences in work absence are reflected in productivity losses, and including such stratifications is important to fully highlight the heterogeneity in those losses. In health economic applications, such as cost-effectiveness and cost-of-illness studies, socioeconomic differences in productivity losses may be larger than the sensitivities in parameter values, such as friction length. Recent methodological contributions on the vacancy multiplier and friction length FCA estimations have made it easier to implement the FCA in health economic applications. These contributions can be complemented by disaggregating these parameters to the group or individual level. With the disaggregation of model parameters in combination with individual-level data, productivity loss analyses will be more realistic and detailed, and their relevance and usefulness will be improved.

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Declarations

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Conflicts of interests Johan A. Liseth Hansen and Thomas Fast are employees of Quantify Research, a consultancy firm providing services to public and private entities, including pharmaceutical companies. Knut Reidar Wangen declares no competing interests.

Availability of data and material Extracted Norwegian register data cannot be shared to anyone outside the study researchers by law. The data used in this study can be applied for through a new application to the data holders.

Ethics approval Ethical approval was obtained from the regional ethical review board in South-East Norway (reference number: 28745).

Consent to participate Not applicable.

Consent for publication Not applicable.

Code availability Provided upon reasonable request.

Author contributions JLH contributed to the study design, data acquisition, analysis, drafting of the manuscript and critical review. TF contributed to the study design, drafting of the manuscript and critical review. KRW contributed to the study design, drafting of the manuscript and critical review. All authors read and approved the final manuscript.

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