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Measuring the Illness-Related Absenteeism – Can Bradford Factor Approximate the Indirect Cost of Illness?

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Abstract

In the management of human resources, the absences are monitored with Bradford Factor (BF) using the number and length of sick leaves. The sick leaves are also measured in health technology to assess the impact of health technologies on product loss, aka indirect cost (IC). Linking the BF and IC might promote BF as an outcome measure and facilitate the estimation of IC. We simulate a single company operation in several scenarios describing the firm's functioning and adjustments to workers' absence. We measure the BF and the IC due to absence and relate them with econometric modelling. Results show that BF and IC are associated in a non-linear way; hence, IC cannot be calculated from BF in a simple manner. The association is strongest for possibility to adjust to worker's absence, and a high elasticity of substitution between workers. Therefore, the possibility to proxy IC by BF is rather limited.

Keywords: Bradford Factor, sick leaves, absenteeism, productivity loss, indirect cost of illness

JEL Classification: D22, J21, L23, M54

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1 Introduction

In the present paper, we study how sick leaves (their number and length) influence firm's functioning in different scenarios and verify if it can be approximated with Bradford Factor — a measure often used in absence management.

Labour remains the production factor with the largest share in the national income, even if it has been falling recently — in 2004 the global adjusted labour income share was equal to 53.7 per cent and decreased to 51.4 per cent in 2017 (Gomis, 2019). Workers absence, especially when unexpected, as when caused by illness, disrupts the functioning of companies. As a result, the affected individual companies are harmed, as they face lowered revenues or perhaps penalties for missing deadlines. In consequence, the aggregated output of the whole economy is diminished. The present paper studies how the two perspective on workers' absenteeism — of the individual company and it's human resource management, and of the aggregate product — are related.

The length of sick leaves varies between countries; among the European countries, it was the largest in Germany (19.9 days in 2019) and the lowest in United Kingdom (4.6 days in 2019) (World Health Organization, 2021). In Poland, it was equal to 14.3 days in 2019 and 15.5 days in 2020. Also work-related injuries and diseases are an economic burden. European Agency for Safety and Health at Work (2017) estimated that global cost of work-related accidents and illnesses amounted to 3.9% of the global gross domestic product (GDP). In the European Union (EU-28), it was equal to 3.3% of GDP. Half of the costs resulted from non-fatal cases, and other half of fatal cases. In Poland, the overall costs (including the indirect, direct, and intangible costs) amounted to 10.4% of GDP and were the highest among such countries as Italy, the Netherlands, Germany, and Finland (Tompa et al., 2021).

From the perspective of a single company, managing the employees' attendance belongs to the task of line management. An element of this process is the monitoring of absences at individual level (Whitaker, 2001). To make this monitoring objective, and comparable across time and employees, a Bradford Factor (BF) was introduced (Armstrong and Taylor, 2020): $BF = S^2 \times D$, where S measures the number of absence spans and D is the total length of these absences, both for a given employee within 52 weeks. How BF originated is uncertain, but it is believed to have been proposed in the early 1980s by the Bradford University School of Management (Bradford Factor Calculator, 2022). BF is calculated for each employee, and its distribution across employees should be monitored to provide a trigger to target appropriate actions (Bevan and Hayday, 2001). When a certain threshold (BF above 45) is exceeded, a company takes action to clarify the reasons. As per definition of BF, numerous short-term absences should be focused on.

An altogether different context in which sick-leaves are also monitored is health technology assessment, i.e. the analysis of health and economic outcomes of health technologies. To understand these outcomes in the widest possible sense, the cost-of-illness studies and cost-effectiveness analyses are sometimes performed from the *societal perspective* (Ernst, 2006). The value of the reduced output, aka indirect cost (IC), is treated as an opportunity cost incurred by the society, as the total amount of goods and services is reduced. In many countries, this societal perspective is indicated as a preferred one in health technology assessment (e.g., in Austria, Denmark, the Netherlands, Norway, Sweden, van Lier et al., 2018).

There are two major methods to estimate IC (Pike and Grosse, 2018): human capital approach (HCA) and friction cost method (FCM). In short, they differ in how the long-term absence is treated (e.g., becoming unemployed due to illness or a premature death): in HCA, the loss is assumed to be generated over the whole time of absence; in FCM, only a friction period is accounted for, in which the economy manages to replace the missing worker (Koopmanschap et al., 1995). In both cases, the IC is estimated by multiplying the absence time (for instance, in days), restricted to friction time in FCM, by the estimate of the product value delivered by a worker per day (for instance, the daily wage) (Berger et al., 2001). In this paper, we consider two scenarios: when the product is reduced for the whole time of a worker's absence, and when a company manages to reorganise its operations if given enough time. In this respect, we study both situations, as modelled by HCA or FCM. In real life, the actual decrease in product may follow a more complicated pattern, because of the impact of one person's absence on other workers (Pauly et al., 2002) or companies taking preventive measures (Jakubczyk and Koń, 2017). It may take some time for the companies to replace a worker, and for this reason the indirect cost may also be driven in particular by short absences. In this sense, the BF and IC may be driven by similar mechanisms.

The aim of the present study is to test to what extent the two measurements — of BF and of IC — are related for various company settings. Establishing such a link would have several consequences. Firstly, the specific formula used to calculate BF would gain additional foundation, which might further motivate its usage in management. In particular, BF changes with the number of sick leaves (when holding the total number of absence days constant). In this paper, we study under what assumptions the estimates of IC have similar property. Secondly, where BF data are available, it might make it easier to estimate the IC from societal perspective. On the other hand, if the link is missing or only present in some cases, it might motivate modifying BF or looking for another index to measure the amount of illness that is more directly associated with actual product loss.

It has been shown that how company and production process is organised impacts the consequences of sick leaves (Grinza and Rycx, 2020). For instance, the absence of workers is more harmful when the work of absent workers is highly interconnected with the duties of other workers. Also the impact of absenteeism is especially high in small businesses. Therefore, we consider various sets of assumptions regarding the production process and replacement of sick worker. In view of this multitude of mechanisms, we decided to use simulations.

We believe that the contribution of the present paper is threefold. First, in the narrow perspective, we present the conditions when two measures of sick leaves are numerically related. This may show when or under what assumptions BF may be used to estimate IC. Second, our results give ideas what alternative to BF could be defined to make it more directly related to IC estimation (we do not consider modifying IC, as it seems to be less arbitrarily defined than BF). Third, in the wider perspective, the present paper demonstrates the need for linking the health economic approach with management theory to understand the economy consequences of health problems. In view of COVID-19 pandemic, the link is indisputable.

The paper is structured as follows. We describe the assumptions in Section 2, along the econometric approach to study the simulation results with the aim of establishing the link between BF and IC. We start with visualising the data and then proceed with Pearson's correlations and econometric modelling. In Section 3, we present the results. In short, we find that there is no link between BF and IC. The discussion follows in Section 4. We briefly conclude in Section 5.

2 Methods

2.1 The production process in the firm

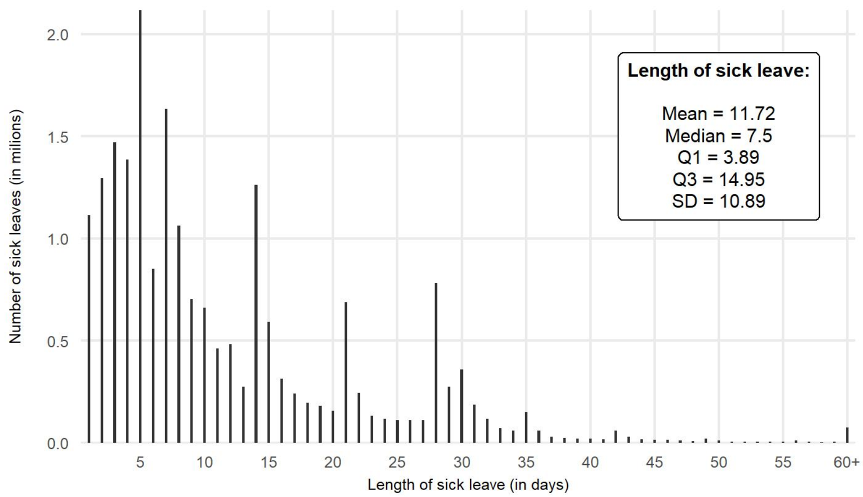
In order to estimate the impact of illness on the firm's functioning, we simulate the production process of a single company over a fixed period of time. BF is not additive over time (i.e., one-year BF is not the sum of two half-year BFs); therefore, the length of this period matters for the results. Typically, it is suggested that BF should be calculated for one year (Armstrong and Taylor, 2020). For this reason, our simulation spans 250 working days, and the time is denoted by $t = 1, 2, 3, \ldots, 250$. This number of working days closely resembles the actual situation in Poland, where there were 251 and 252 working days in 2022 and 2021, respectively (Infor, 2020, 2021).

In the production function, we consider the labour force (L) to be the only production factor. In the short term that we consider, neglecting the capital accumulation etc. is warranted. We also assume the company does not change its workforce during the simulation period (other than because of absenteeism or replacements, as described below). Therefore, the size of the firm is fixed, and firms of various sizes are considered (as described in details below).

Every working day, a healthy worker may get sick with probability s. The duration of illness is random: it is picked from the actual empirical distribution of sick leaves in Poland in 2021 (Zakład Ubezpieczeń Społecznych, 2022c; Fig. 1), with an exception that we limit the maximum length of a leave to 182 days, as the reported values are censored at this value. If the length of the sick leave exceeds the total remaining simulation time, the length of the sick leave is reduced to the number of days until the end of the simulation. We use the distribution of individual sick leaves for people who were insured in Social Insurance Institution (Polish: Zakład Ubezpieczeń

Społecznych, ZUS); such sick leaves amounted to 83% of all sick leaves in Poland (Zakład Ubezpieczeń Społecznych, 2022a).

Figure 1: The duration of individual sick leaves in Poland (2021). For the presentation purpose, we aggregated sick leaves exceeding 60 days



The output of the firm is calculated separately each day and is denoted by Y_t. We assume the following CES-type (Saito, 2012) production function to be applied in each period, indexed with t:

$$Y_t = (\sum_{l=1}^{L} x_{l,t}^{\rho})^{1/\rho}, \tag{1}$$

where:

L measures the number of workers in company in total,

$x_{l,t}$ measures the amount of labour generated by l-th worker in period t, depends on worker's absence and duty sharing between workers, $x_{l,t} \in [0, 1]$,

ρ is a elasticity of substitution parameter.

2.2 Simulation parameters

To measure the relation between BF and IC across a variety of settings, we differentiated several of the parameters in the simulation. We vary:

- the values of probability of becoming sick, $s \in \{0.01, 0.02, \ldots, 0.05\}$,

– the number of workers, $L \in \{5, 10, 50, 250\}$,

– the elasticity of substitution parameter in the production function, $\rho \in \{0.25, 0.5, 0.75, 1\}$.

Based on available data, it is difficult to precisely estimate the actual values of s. The range of values we use was based on the following reasoning. At the end of 2020, the number of people working in the Polish national economy equalled 16 million (Główny Urząd Statystyczny, 2021), and there were 256 million days of sick leaves in 2020 with the average length of sick leave equal to 12.4 days (Zakład Ubezpieczeń Społecznych, 2022b). Assuming that each worker worked whole year, we can conclude that probability that worker will be absent on given day was equal to 4% (256 million days divided by 16 million divided by 365 days). As it is not exactly the same as parameter s (s is probability that healthy worker will get sick, not the probability that worker will be absent in given day), in the simulations, we used several values close to 4%.

In our simulations, we decided to use the number of workers in the company that describe micro, small, medium-sized and large companies (European Commission, 2020), i.e. companies hiring 1–9, 10–49, 50–249, 250 and more workers .

The simulated values of ρ spanned over the whose sensible range: we considered both companies with perfect substitution of workers (corresponding to $\rho \approx 1$) and companies with a production function close to Cobb-Douglas ($\rho \to 0$) (Saito, 2012).

For each combination of parameters (i.e. $80 = 5 \times 4 \times 4$ combinations) and for each scenario of how a firm can adjust to workers absence (described in the next subsection), we simulated the one-year firm's functioning 1000 times.

2.3 Firm's adjustment to worker's absence

We consider three scenarios regarding how a firm may respond to the absence of employees.

No adjustments In this scenario, we consider one extreme: the firm does not react to the employee's absence. The sick leave simply results in total loss of productivity for the whole period of the absence, i.e. $x_{l,t} = 0$ for an absent worker. The individual productivity of present workers is not affected, i.e. $x_{l,t} = 1$ for present workers.

Worker's replacement after a friction period In this scenario, the firm's capacity due to a worker's absence is fully reduced only during a friction period (FP). After FP, the firm rearranges its operation so that the absence does not longer affect the output. Such reorganisation assumes hiring new or temporary worker who will fully take over duties of absent worker, and FP represents the time needed to organise the replacement. We consider FP equal to $10, 12, \ldots, 30$. In consequence, for worker l getting sick in time t, we have $x_{l,t} = 0$ for $t \leq FP$, and $x_{l,t} = 1$ for $t > FP$. Other workers are not affected, i.e. $x_{l,t} = 1$ for worker l who is healthy in period t.

Duty sharing between workers In this scenario, we consider a somewhat intermediary situation to the above two scenarios. An absent worker can be replaced, yet the replacement is done internally, using the existing firm's capacity, i.e. some of the duties of absent worker are initially taken over by other employees and only after FP the firm can replace the absent worker with external replacement. In consequence, for worker l getting sick in time t we have $x_{l,t} = r$ for $t \leq FP$. For worker other then l who is present at work at period $t \leq FP$ we have $x_{l,t} = 1 - r/L_h$ where L_h refers to number of healthy (present) workers at period t. For $t > FP$, $x_{l,t} = 1$. We consider $r \in (0.25, 0.5, 0.75)$ and $FP \in (10, 12, \ldots, 30)$.

2.4 Output measures

For each run of a simulation for a given set of parameters L, ρ, s, FP, r we calculate two output measures: BF and its constituents (i.e. the number of sick leaves and the total length of these sick leaves) and the IC. The latter is calculated in the following way. For each day of a worker's absence, we subtract the actual firm production on this day from a hypothetical production that would have been obtained if this worker had been present on this day. These differences are then aggregated over the whole 250 days for each worker.

2.5 Econometric approach to studying the relation between BF and IC

Exploration of the simulation results First, we visualise on the scatter plots the relationship between BF and IC according to different values of parameters. As in many cases points overlap, we present with solid line convex hull (calculated with algorithm developed by Eddy, 1977) of points according to the value of each parameter to show the range of BF and IC values for each value of parameters. We also calculated the Pearson's linear correlation coefficient between each parameter and output measures — BF and IC. Then to measure the relationship between BF and IC, we calculated R^2 of the following model:

$$\ln(BF) = \beta_0 + \ln(IC) + \epsilon. \tag{2}$$

Such model was built for the given set of analysed parameters. To verify which of the parameters has influence on the R^2 (i.e. relationship between BF and IC), we built a following meta model:

$$R^2 = \beta_0 + L + \rho + s + FP + r + \epsilon. \tag{3}$$

In the scenario with no adjustments parameters FP and r and parameter r in the scenario with full adjustment after FP were discarded from the model.

Econometric approach on the level of individual worker To assess the relation between the BF and the IC we studied the relation between IC and the constituents of BF, i.e. S and D on the level of individual workers. Assuming IC and BF are associated with a non-linear, power transform, would yield:

$$IC = \alpha_0 \times \left(S^2 \times D\right)^{\alpha_1}. \tag{4}$$

We take the logarithm of both sides to use a linear regression with the following model specification:

$$\ln(IC) = \beta_0 + \beta_1 \times \ln(S) + \beta_2 \times \ln(D) + \epsilon, \tag{5}$$

where IC, S, and D are calculated per individual worker for a given simulation run of a single firm (i.e. 250 days in a firm), and the following relation between the model parameters and the hypothesised relation between BF and IC (Eq. 4) hold:

i) $\beta_0 = \ln(\alpha_0)$,

ii) $\beta_1 = 2 \times \alpha_1$,

iii) $\beta_2 = \alpha_1$.

We build separate models for each set of parameters and each of 1000 simulation runs. Therefore, we obtain 80 (5 values of s × 4 values of L × 4 values of ρ), 880 (5 values of s × 4 values of L × 4 values of ρ × 11 values of FP) and 880 (5 values of s × 4 values of L × 4 values of ρ × 11 values of FP) and 2640 (5 values of s × 4 values of L × 4 values of ρ × 11 values of FP × 3 values of r) vectors of estimated βs respectively for scenario with no adjustments, for scenario with worker's replacement after a FP and duty sharing between workers. We estimate model parameters using the least squares method based on the simulations where $IC, S, D > 0$, as we want to look for relationship between BF and IC, so we are only interested in situations where there is at least one absence.
If IC was proportional to BF, then we expect $\alpha_1 = 1$, and so $\beta_1 = 2$ and $\beta_2 = 1$. If IC was a power transform of BF, then we expect $\beta_1 = 2 \times \beta_2$. Otherwise, we conclude no simple relation holds between BF and IC.
All the analyses were conducted in R, version 4.1.3 (R Core Team, 2022).

3 Results

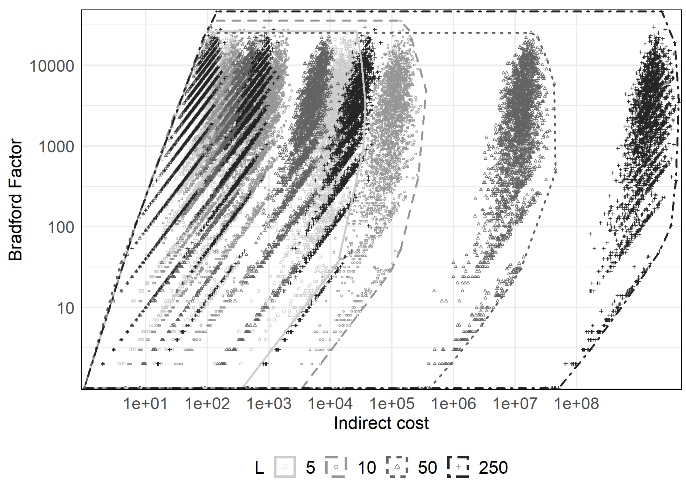
3.1 No adjustments

As there are no adjustments in this scenario, the simulations differ with respect to three parameters: s, L, and ρ. To understand their impact on the BF and IC, we first present the results of simulations — the BF and IC per individual workers — in three panels of Fig. 2, visually splitting the results per individual values of respective parameters. For clarity, we only presented a random sample of 500 points (a random selection of 100 simulations and a random sample of 5 workers in each — we want to present the same number of points for each set of parameters and 5 is the smallest number of workers among considered values of parameters).

First, as it is intuitive per model construction, both L and ρ impact the IC only, and not the BF (in the respective panels, the clouds of points corresponding to smaller values of ρ or larger values of L are located more to the right). The interpretation of the impact of ρ is rather straightforward: when workers' input is more complementary, i.e. smaller ρ, a single worker's absence has more impact on the product of the whole company. For L, a similar explanation holds: in larger companies, the absence of a single worker has impact on the productivity of more other workers.

Figure 2: Bradford Factor and production loss due to worker's absence in the scenario when the firm does not adjust to worker's absence according to different simulation settings

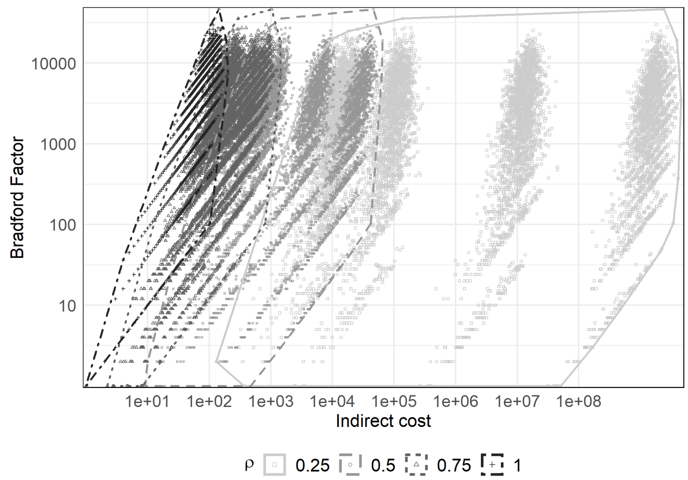
(a) Parameter: L



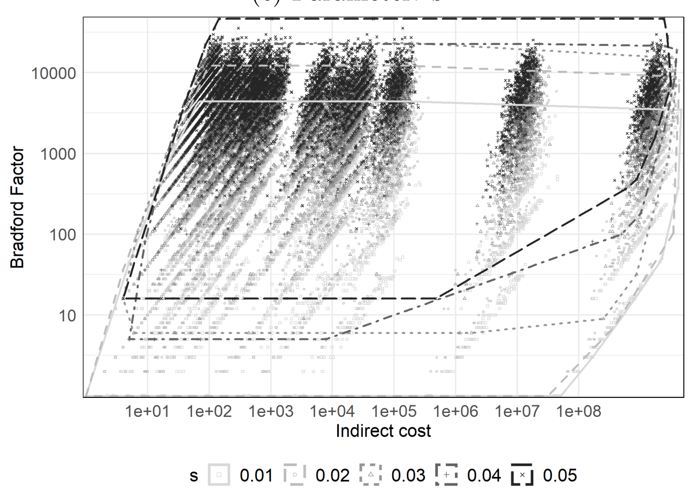
Interestingly, the parameter s seems to impact BF more strongly than IC, i.e. the clouds of points for larger values of s are located more to the top of the figure. Such observation confirms values of Pearson's correlation coefficients (Tab. 1) that show that s is significantly correlated with both BF and IC and the strength of correlation is higher in case of BF (0.636 vs. 0.017).

Figure 2: Bradford Factor and production loss due to worker's absence in the scenario when the firm does not adjust to worker's absence according to different simulation settings, cont.

(b) Parameter: ρ



(c) Parameter: s



Note: A single point presents a single simulation run for a single employee's 250-day working period. Polygons present convex hulls for set of points resulting from given value of parameter. For each setting of parameters L, ρ, s results of 100 simulations for 5 workers are presented. Also for both axis logarithmic scale was used.

Table 1: Pearson's correlation coefficients with p-values (in brackets) between parameters s, L, ρ and BF, IC in the scenario when the firm does not adjust to worker's absence

Variable	BF	IC
L	0.001 (0.041)	0.222 (< 0.001)
ρ	0.000 (1.000)	− 0.591 (< 0.001)
s	0.636(< 0.001)	0.017 (< 0.001)

The parameters L and ρ are defined on a firm level. Additionally, L explicitly depends on the firm's decisions (and ρ as well to some extent, Brynjolfsson and Milgrom, 2012). Meanwhile, in a single company there may be workers facing different values of s, for instance, due to different risk factors (e.g., age, life-style, comorbidities). Therefore, it is warranted to analyse the data for all s values pooled. When looking at the points corresponding to a specific combination of L and ρ, a positive association between BF and IC can be seen (Fig. 3), and the association seems stronger, when data are further analysed in the subgroups defined by s. In Tab. 2 we present the results of the meta model explaining R^2 with parameters L and ρ and s, where R^2 refers to the model explaining the logarithm of BF with the logarithm of IC. According to the results of the meta model, in the scenario when the firm does not adjust to worker's absence, the association between BF and IC is stronger (R^2 is the highest) the lower value of s and the higher value of ρ is. Mean value of R^2 equals 0.679 with median value 0.709.

Table 2: Results of meta model explaining R^2 (of model explaining the logarithm of Bradford Factor with the logarithm of the indirect cost) with parameters L, ρ, s in the scenario when the firm does not adjust to worker's absence

Variable	Estimate	SE	p-value
Intercept	0.811	0.013	< 0.001
L	0.000	0.000	0.002
ρ	0.075	0.014	< 0.001
s	−6.267	0.275	< 0.001

To show the results of the relation between IC and BF in more details, we inspect the results of the econometric analysis defined in Subsection 2.5, looking into the constituents of BF, i.e. S and D. To see how the work organisation and risk of illness impact the result, we use the same split per L, ρ, and s in three panels of Fig. 4, to present the results (i.e. β_1 and β_2) for the 80 models.

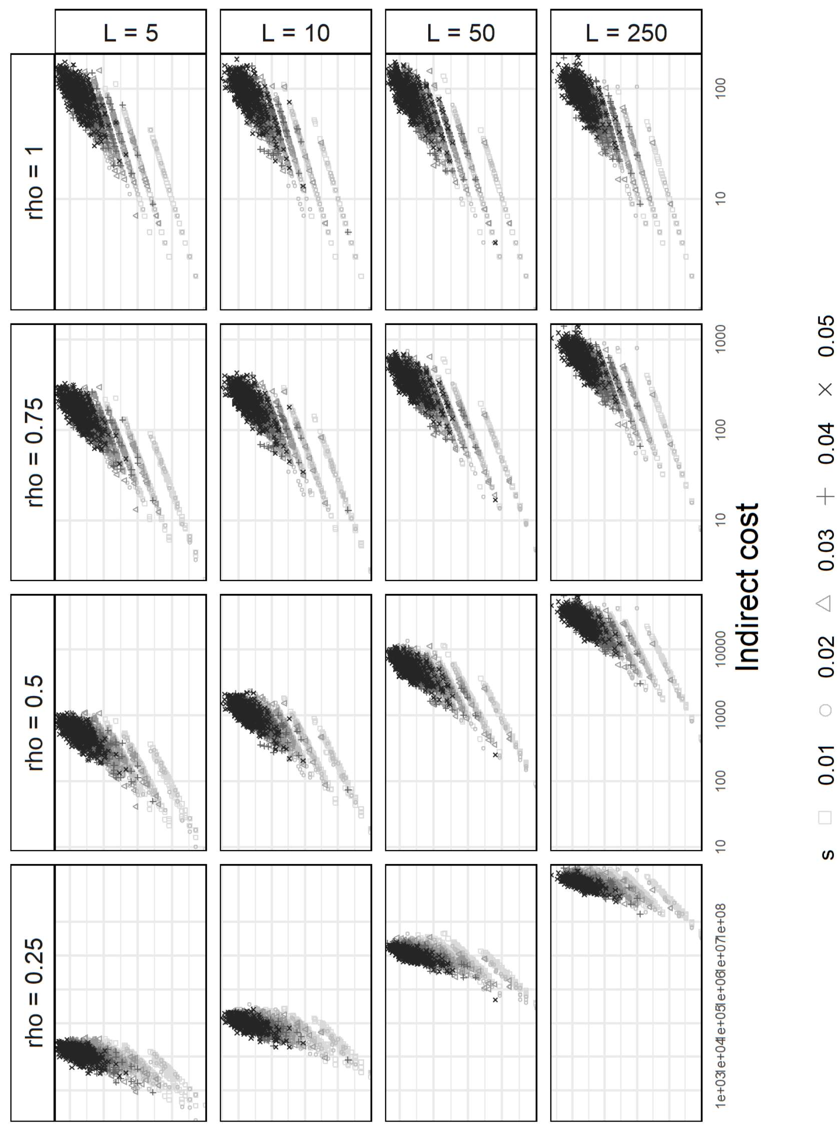
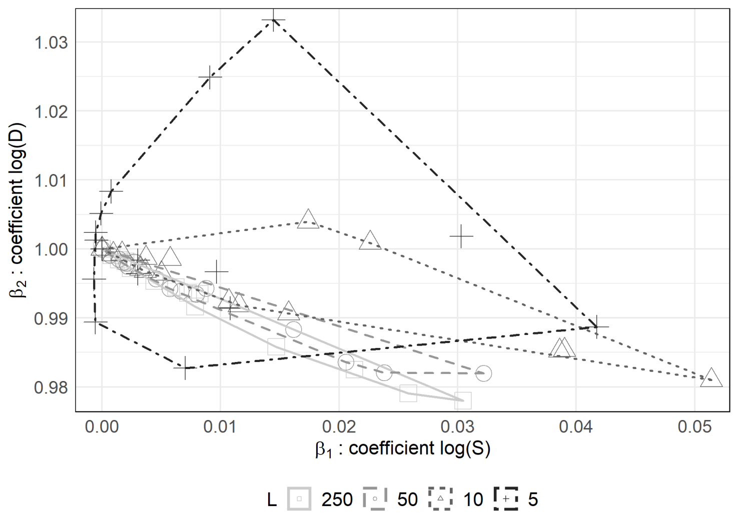


Figure 3: Bradford Factor and production loss due to worker's absence in the scenario when the firm does not adjust to worker's absence according to different simulation settings

Figure 4: Coefficients of the sum of the number of sick leaves (S) and the sum of the duration of sick leaves (D) when the firm does not adjust to worker's absence according to different simulation settings

(a) Parameter: L



(b) Parameter: ρ

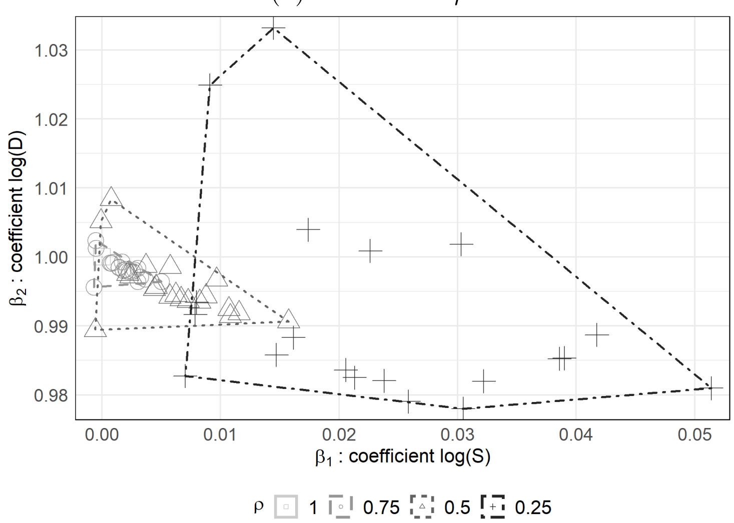
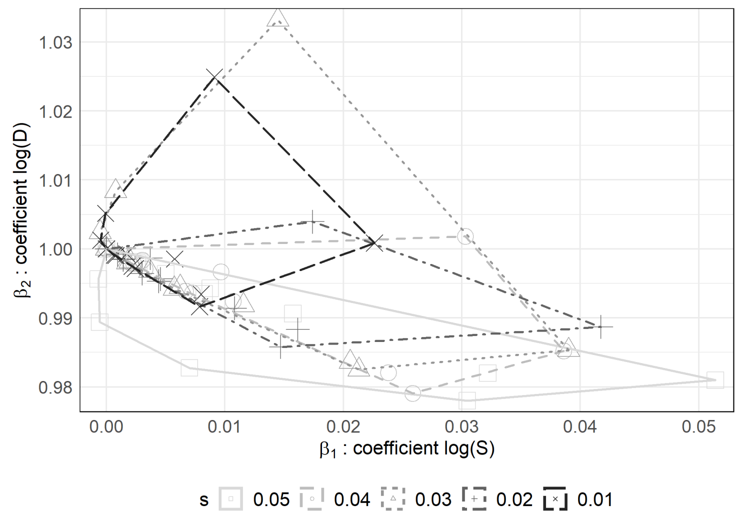


Figure 4: Coefficients of the sum of the number of sick leaves (S) and the sum of the duration of sick leaves (D) when the firm does not adjust to worker's absence according to different simulation settings, cont.

(c) Parameter: s



Note: Polygons present convex hulls for set of points resulting from given value of parameter.

The results suggest that the number of illness spans (S) is only very weakly related to IC (i.e. β_1 are very close to 0). Nevertheless, the impact is non-zero, which means that it is not only the total duration (D) that affects the IC. The impact of S is larger for larger s (i.e. bigger risk of illness) and smaller ρ (i.e. greater complementarity of workers). The impact of D is almost perfectly linear, i.e. $\beta_2 \approx 1$. It seems that the impact is slightly less than proportional for larger firms (i.e. larger L). For any firm's settings, IC cannot be directly explained by (a nonlinear transformation of) BF.

3.2 Worker replacement after a friction period

In Fig. 5, we present the results for this scenario in a way similar to Fig. 2 in the previous subsection. There is one more panel, corresponding to the FP parameter (which was not present in the previous subsection). The conclusions regarding the impact of L, ρ, and s are similar to those presented in the previous scenario. In case of FP, the larger values seem to increase the IC without impacting BF, which confirms the intuition behind the model construction. Such observation confirm Person's correlation coefficients and also shows that in the scenario, when absent worker is fully replaced after FP, correlation between FP and BF is non-significant and correlation between FP and IC is statistically significant (Tab. 3).

Table 3: Pearson's correlation coefficients with p-values (in brackets) between parameters s, L, ρ, FP and BF, IC in the scenario when the firm fully adjusts to worker's absence after FP

Variable	BF	IC
L	0.001 (< 0.001)	0.227 (< 0.001)
ρ	0.000 (1.000)	− 0.604 (< 0.001)
s	0.636 (< 0.001)	0.049 (< 0.001)
FP	0.000 (1.000)	0.010 (< 0.001)

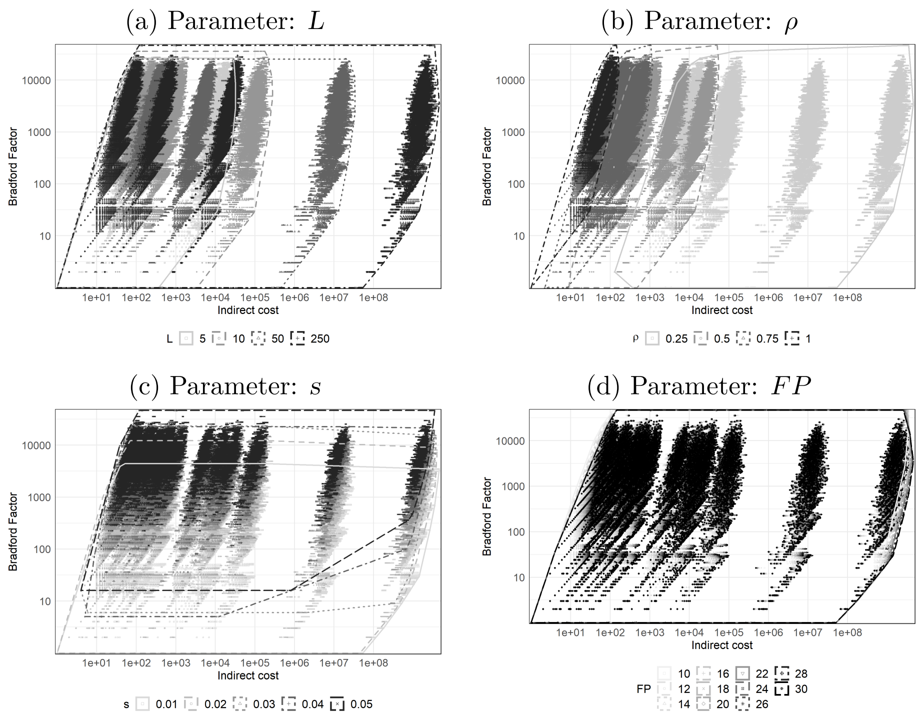
Table 4: The results of a meta model (explaining the R^2 of a model linking the logarithms of Bradford Factor and indirect cost) with parameters L, ρ, s, FP in the scenario with full adjustment after friction period

Variable	Estimate	SE	p-value
Intercept	0.954	0.006	< 0.001
L	0.000	0.000	< 0.001
ρ	0.083	0.005	< 0.001
s	−3.511	0.095	< 0.001
FP	−0.007	0.000	< 0.001

Mean value R^2 of the model explaining BF with IC in the scenario when firm adjust fully after FP equals to 0.775 with median value 0.797. The results of the meta model explaining R^2 show that the relationship between IC and BF is the strongest for low values of FP. Also increase in FP deteriorates the relationship between IC and BF (Tab. 4). In comparison to the scenario with no adjustments, the influence of s on R^2 is smaller.

The results of econometric modelling to associate IC to the constituents of BF are presented in Fig. 6. In the current scenario, the findings differ substantially from the previous scenario. For many values of parameters, the impact of D is much less than proportional (i.e. $\beta_2 < 1$) and the impact of S is non-negligible (i.e. $\beta_1 > 0$). In the present scenario, we added a black solid line to the graphs showing where the relation between the parameters would correspond to the IC being a power transform of BF ($\beta_1 = 2 \times \beta_2$). For short time of FP the estimated values are close to this line (see the bottom right panel of Fig. 6), which shows that when the workers can be quickly

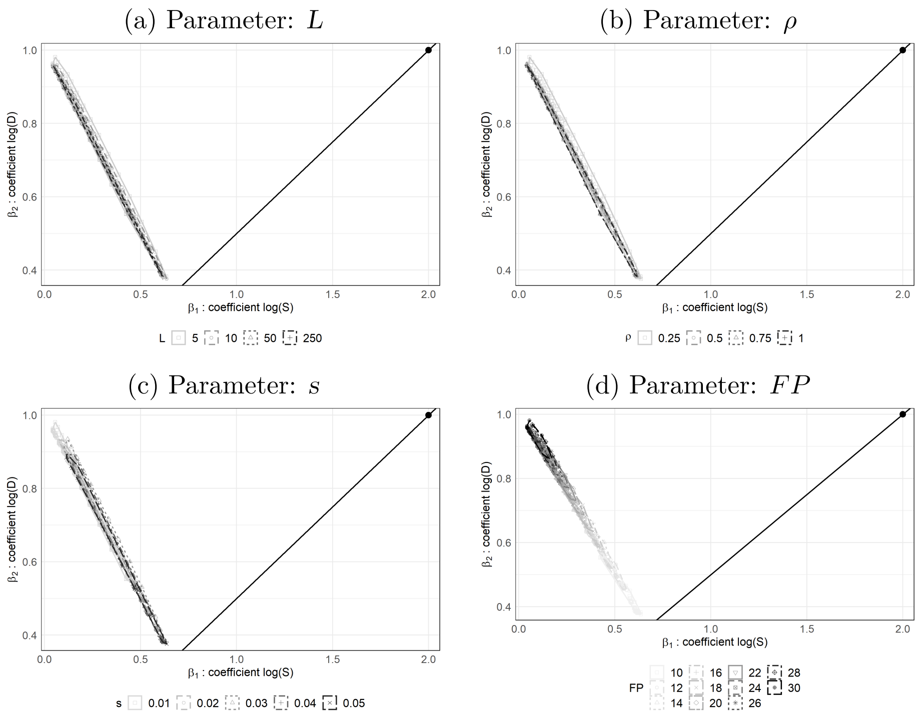
Figure 5: Bradford Factor and production loss due to worker's absence in the scenario when the firm fully adjusts to worker's absence after FP according to different simulation settings



Note: Point refers to one simulation of employee's 250-day working period. Polygons present convex hulls for set of points resulting from given value of parameter. For each setting of parameters L, ρ, s, FP results of 100 simulations where BF and production loss are greater than 0 for 5 workers are presented. Also for both axis logarithmic scale was used.

replaced (say, in about less than 2 weeks), the BF and IC are directly related (even if via a non-linear link).

Figure 6: Coefficients of the sum of the number of sick leaves (S) and the sum of the duration of sick leaves (D) with full adjustment after friction period



Note: Polygons present convex hulls for set of points resulting from given value of parameter.

3.3 Duty sharing between workers

In the present scenario, the results resemble those in the previous one, see Fig. 7 with additional panel for r parameter. Among parameters L, ρ, s, FP and r only s is significantly correlated with BF (Tab. 5). All of the parameters correlate with IC. It is difficult to discern the impact of the r parameter (i.e. parameter referring to the duty sharing between absent and present workers) as the r has no impact on the relationship between IC and BF (Tab. 6). That confirms the last panel of Fig. 8, where results of the models does not differ between different values of r. The mean

R^2 of the meta model explaining logarithm of BF with the logarithm of IC equals 0.776 and the median equals 0.799.

Figure 7: Bradford Factor and production loss due to worker's absence with full adjustment after friction period and taking over some of the duties of sick worker during FP according to different simulation settings

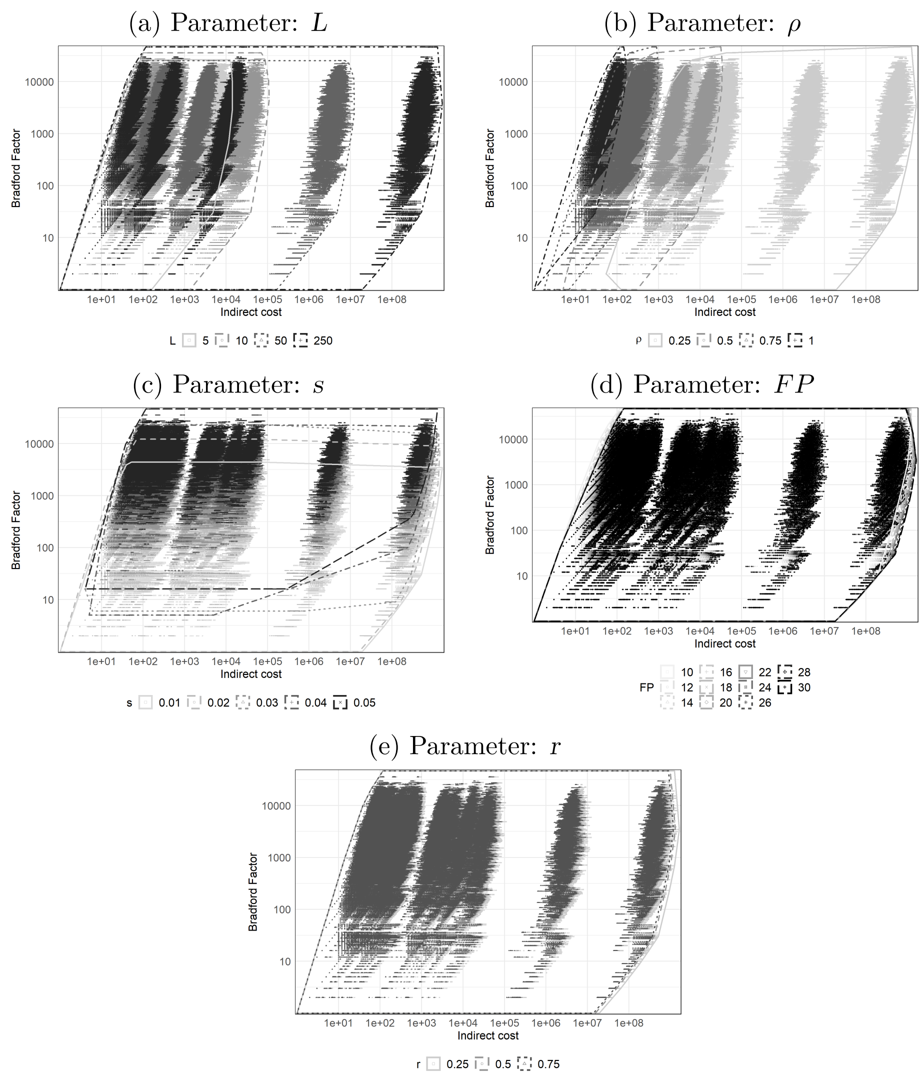


Figure 8: Coefficients of the sum of the number of sick leaves (S) and the sum of the duration of sick leaves (D) with full adjustment after friction period and taking over some of the duties of sick worker during friction period according to different simulation settings

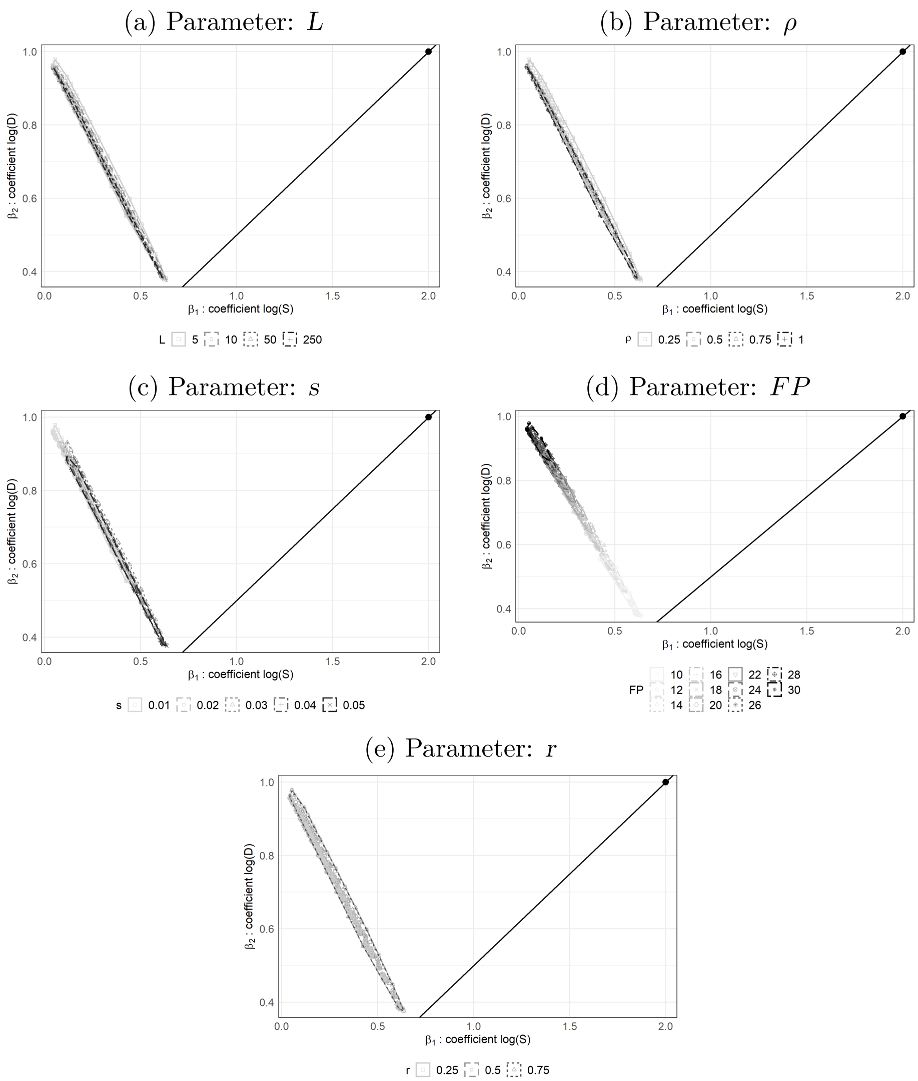


Table 5: Pearson's correlation coefficients with p-values (in brackets) between parameters s, L, ρ, FP, r and BF, IC with full adjustment after friction period and taking over some of the duties of sick worker during FP

Variable	BF		IC	
L	−0.001	(< 0.001)	0.255	(< 0.001)
ρ	0.000	(1.000)	− 0.564	(< 0.001)
s	0.650	(< 0.001)	0.046	(< 0.001)
FP	0.000	(1.000)	0.009	(< 0.001)
r	0.000	(1.000)	− 0.056	(< 0.001)

Table 6: Results of meta model explaining R^2 (of model explaining the logarithm of Bradford Factor with the logarithm of the indirect cost) with parameters L, ρ, s, FP, r in the scenario with full adjustment after friction period and taking over some of the duties of sick worker during FP

Variable	Estimate	SE	p-value
Intercept	0.959	0.004	< 0.001
L	0.000	0.000	< 0.001
ρ	0.075	0.003	< 0.001
s	−3.458	0.051	< 0.001
FP	−0.007	0.000	< 0.001
r	0.002	0.000	0.613

4 Discussion

In the study, we verified the relationship between the IC and BF for various parameters describing firm's functioning. The results show that there is no linear relationship between those two measures. For certain sets of parameters the relationship is non-linear. A particularly important parameter is FP that describes firm's ability to adjust to worker's absence — if firm can quickly (in less than 10 days) replace absent worker then a non-linear relationship between BF and IC is observed.

In the study, we considered various types of production function. Among others, we analysed different values of the elasticity of substitution of production factors. In firms where there is no perfect substitution of workers, we expect production based on teamwork. The collective nature of the production is indicated as a relevant factor of the indirect cost of illness (Krol et al., 2012). Including teamwork in analysis of the impact of illness of firm's functioning was also provided e.g. by Pauly et al. (2002), who indicates (based on a formal microeconomic model) that indirect cost of illness is particularly high when the work is organised as a team (the absence of one team member can significantly affect the productivity of the entire company). Our results are consistent with their findings, as IC was positively correlated with parameter describing elasticity of the worker's substitution.

The very construction of the Bradford Factor may raise controversy. It is indicated in management as a tool to measure employee absenteeism in the company. However, it is important to notice that this indicator does not take into account any specific factors such as disability and diseases that cause short systematic absences. Also Munir et al. (2008) shows that policies focusing only on the worker's absences are troublesome for people with chronic disease and can increase presenteeism and cause long-term sick leaves. Those disadvantages of BF do not concern our study, as our goal is not to evaluate a specific employee, but only to examine the property of a certain measure used in human resources management.

In our study, we use parameters with values close to those observed in Poland (and the distribution of the duration of sick leaves was exactly based on Polish data). We believe that as we analyse relation between variables (rather than absolute values), similar results would be observed for other countries.

In the simulation, we used the distribution of sick leaves in 2021, the year when there was still COVID-10 pandemic. We believe that the choice of the year does not affect the results, as pandemic caused several changes in the absenteeism. On one hand, people were sick from the COVID-19, and on the other hand there were fewer infectious diseases and the access to health care was limited. Also remote type of work became more popular, that could cause some people to work from home, even though they were sick.

The main limitations are as follows. Firstly, firm parameters used in the simulation were not exogenous, especially L (but also perhaps the replacement mechanism). In reality, the companies can optimally select how they function, accounting for market situation but also for internal constraints, including sick leaves. Also, firms can optimise their functioning based on the expected sick leaves and therefore minimise the IC (Jakubczyk and Koń, 2017). Including firm's adjustment to possible absence possibly would impact IC and it's relationship with BF.

Secondly, as it was beyond the scope of the paper, we did not look at the profit aspect of the company. The indirect cost are measured from the societal perspective, and they are not equivalent to the losses of the company. For instance, if the company manages to maintain the product by paying extra to its (healthy) employees to make them make up for the sick ones, it harms the company's profit but it actually reduces the indirect cost.

Thirdly, we only simulated a single company. In actual markets, the competing companies act as substitutes and a reduced potential of one can be made up by others. This is especially true for some businesses. For instance, if a restaurant in the main square of a city is closed due to illness, the customers can rather easily satisfy their demand in neighbouring eateries. On the other hand, some companies may be

linked in a complementary way (for instance restaurants in shopping centres). Closing one business can affect the functioning of other business.
We also did not possible infections between employees. Then for the higher L there may be more infections, which could change the relationship between BF and IC.
Moreover, in our paper we consider indirect cost of illness only in terms of absenteeism and ignore presenteeism. However, it seems justified to consider that before or after the sick leave the worker can have reduced productivity or can be sick at work.

5 Conclusions

Measuring the illness-related absenteeism is important for various purposes. BF and IC are two measures coming from the management and the health economics contexts, respectively. The association between the two, however, is poor. A non-linear transformation between the two holds in some settings (when firm can quickly adjust to worker's absence) and in such situations one can be used to approximate the other.

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