Monitoring and Sickness Absence Behaviour: Who Goes Back to Work Rather Than Visit the Doctor?

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Introduction

Paid sick leave from work is a right in most developed countries

- Shields individuals from the income effects of health shocks, allows consumption smoothing

How to best design the system?

- Monitoring used to make sure that workers return to their jobs when healthy enough to do so
- Opportunity cost of medical professionals' time is high
- Can it be cost-efficient to reduce monitoring of individuals whose sickness absence it does not affect?
- Sickness insurance/absence salient issue during the Covid-19 pandemic as countries relaxed rules (OECD 2020)

This Paper

What characterises workers with different sensitivity to monitoring?

- Setting: unique randomised controlled experiment
- Estimate causal effects of monitoring on sickness absence

Heterogeneity analysis using GRF (Athey et al., 2019)

- Fully data-driven, tests for heterogeneity across large number of covariates and thresholds, avoids overfitting, nonparametric

Findings:

- Those who react strongly to monitoring have high past sickness absence, low socioeconomic status, are men, live in poor neighbourhoods, have peers with high sick leave uptake
- Possible to be more cost-efficient with a targeted monitoring policy - if desirable

Background

We know quite a lot about the patterns of sickness absence...

- Sickness absence higher among women (Paringer, 1983), public sector employees (Frick and Malo, 2008), low-paid workers (Barmby et al., 2002), non-key workers (Hensvik and Rosenqvist, 2019), large workplaces (Winkelmann, 1999), certain neighbourhoods (Lindbeck et al., 2016)...
- But is high sickness absence in a group connected to higher sensitivity to monitoring?
- Large cross-country differences in sickness absence
- Reducing/increasing income replacement rates decreases/increases absenteeism, absenteeism falls after first day of absence excluded from coverage (Henrekson and Persson, 2004; Johansson and Palme, 2005; Ziebarth and Karlsson, 2010; Böckerman et al., 2018)

Background

...but quite little about how workers react to monitoring

- Studies based on public sector workers in Italy (Boeri et al., 2021) and a Norwegian municipality (Ferman et al., 2023) arrive at opposite conclusions
- Earlier work on the Swedish experiment: Hartman et al. (2013); Hesselius et al. (2013); Johansson et al. (2019)

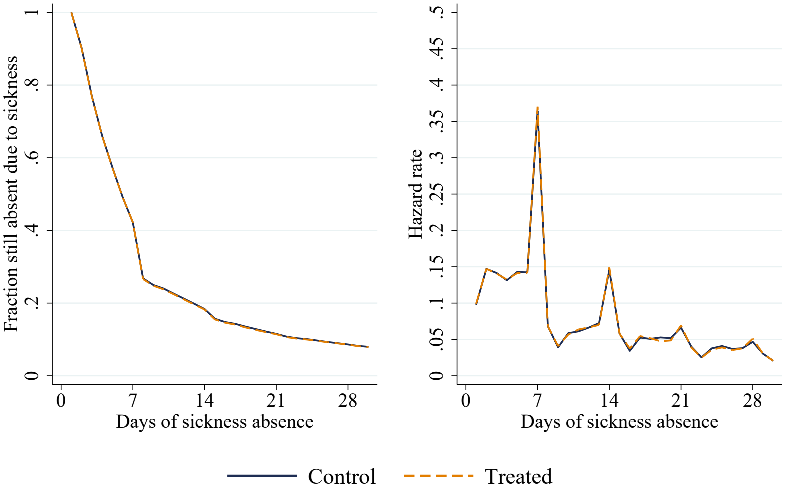
The Experiment

Randomised controlled trial in two Swedish regions (Gothenburg city and Jämtland region) in July-December 1988

- 270 000 insured individuals affected
- *Controls* (born on odd dates) could take out 7 days of sick leave before providing a doctor's certificate; *Treated* (born on even dates) could take out 14 days of sick leave before providing a doctor's certificate
- Seen as unsuccessful due to substantial increase in sickness absence among the treated

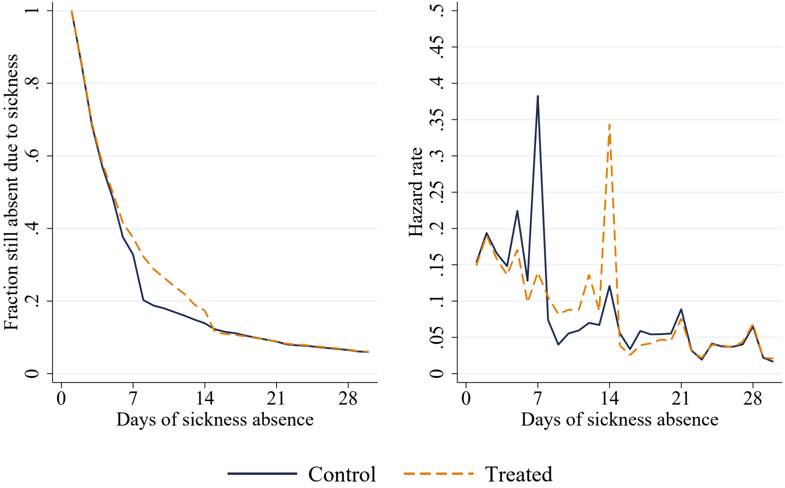
Map | Sickness insurance system during the experiment

Before the Experiment



Propensity score histogram

During the Experiment



Data

Individual-level register data

- All sickness absence spells before, during and after the experiment; allow for detailed description of workers' families, careers, socioeconomic status, neighbourhoods...
- Only employed individuals; workers in the central government sector not part of the experiment and are excluded

Outcome: duration of sickness absence spell in days

- Probability of sick leave spell ending on days 8-14 gives very similar results

Heterogeneity Analysis: GRF (Athey et al, 2019)

Traditional approach: Researcher splits sample based on a characteristic and threshold of interest

GRF: Splits the sample based on the variables and threshold values which maximise treatment effect heterogeneity

- Aggregates a large number of **causal trees** - each tree is based on a random subsample of individuals

Advantages of GRF:

- Can analyse many variables and thresholds, identifies relationships which hold consistently across subsamples (no overfitting), flexible with regard to functional form, tolerates missing values

When estimating: Split into **training set** (80 % of families) and **held-out test set** (remaining 20 %) Implementation details

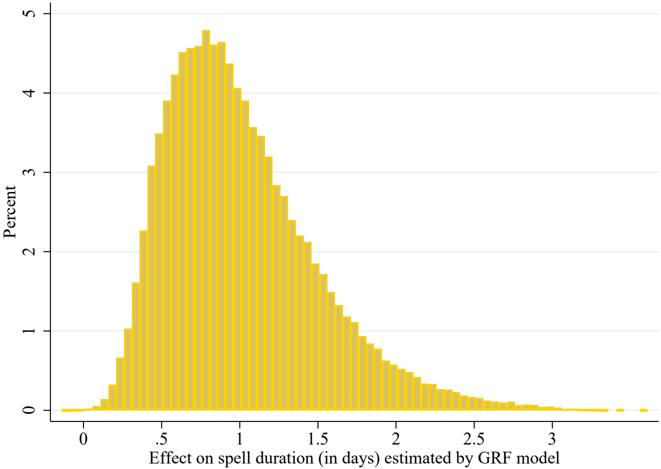
Potential Drivers of Sickness Absence

Aim to include as many factors that have been identified as connected to sickness absence by previous literature as possible

Literature

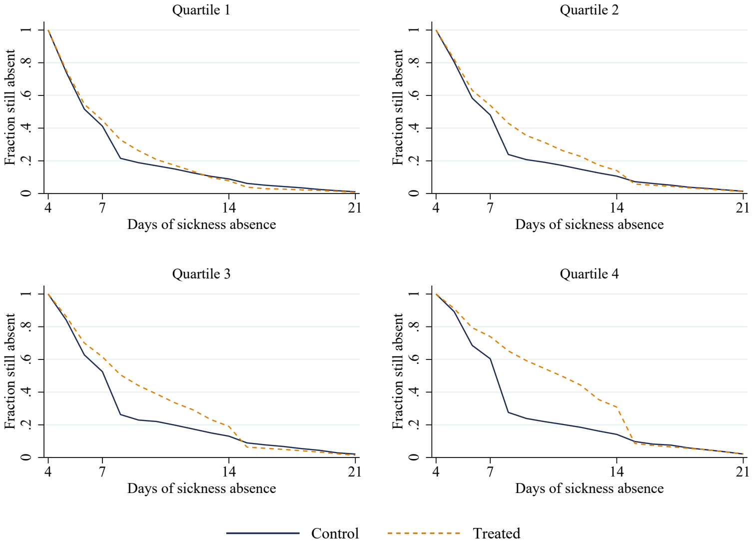
- **Demographics**: age, gender, immigrant background
- **Family**: marital status, share of family income, N children, days spent caring for sick children, partner's pre-period sick leave...
- **Career**: education, L income, share income from main job, from self-employment, from social payments, industry dummies, public sector...
- **Workplace**: N employees, income rank, tenure, average sick leave...
- **Neighbourhood**: socioeconomic characteristics, average sickness absence...
- **Health** (pre-experiment): Days sickness absence, N short absence spells...

Treatment Effect Estimates



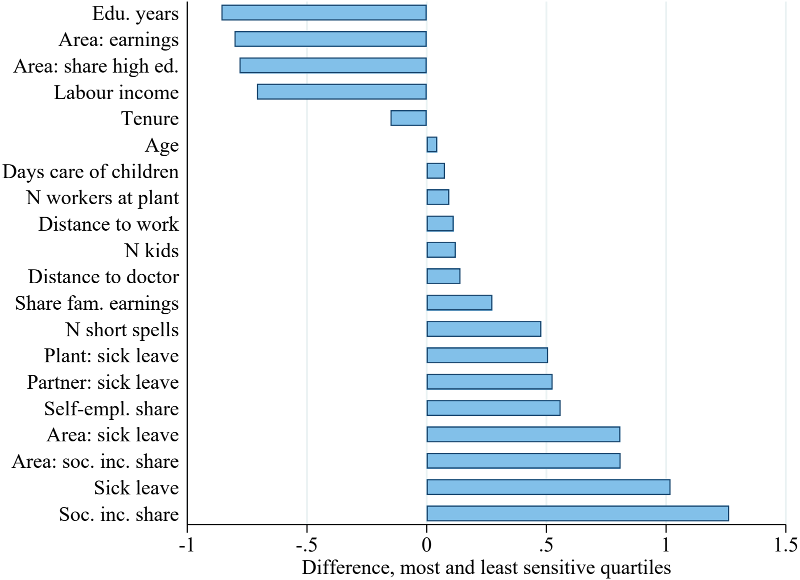
BLP test | Pr(Return to work in week 2) as outcome | Comparison to Lasso

Validation on the Test Set

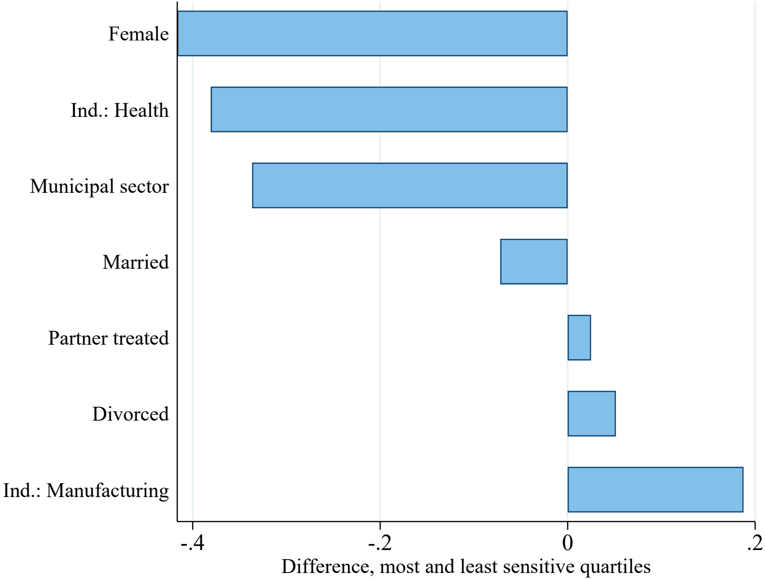


Hazard graphs

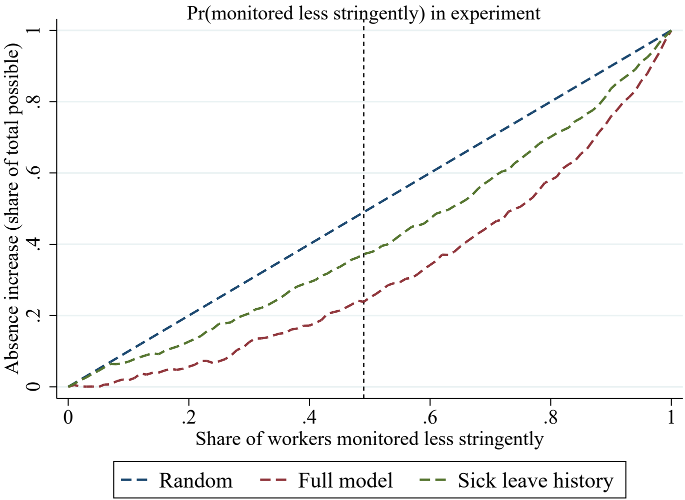
Who Reacts to Monitoring? (Selected Variables)



Who Reacts to Monitoring? (Selected Variables)

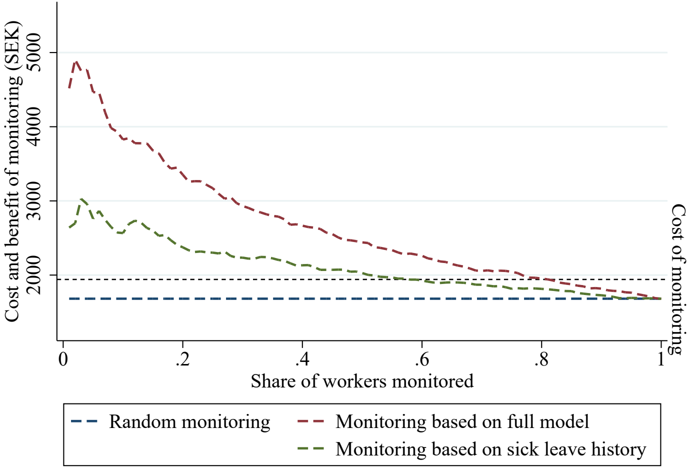


Targeted Monitoring Policy



Comparison to LASSO | Policy tree | QINI of different policies

Cost-Benefit Analysis



Assumptions: cost of visit=1941 SEK (≈ 190 EUR, from Västra Götaland region),

benefit=reduction in days of absence × "daily wage" including payroll tax

Concluding Remarks

Use GRF to study whether it is efficient to relax sickness absence monitoring in a targeted way

- Analyse a large number of characteristics at the same time in a data-driven way

Workers who are sensitive to monitoring:

- Have high sick leave uptake in previous periods, low socioeconomic status, are men, live in socioeconomically disadvantaged neighbourhoods, have peers with high sick leave uptake

If monitoring is targeted:

- Same reduction in share of workers monitored as in the experiment can take place at half the cost in terms of increased absence
- Estimated to be cost efficient, unlike non-targeted monitoring

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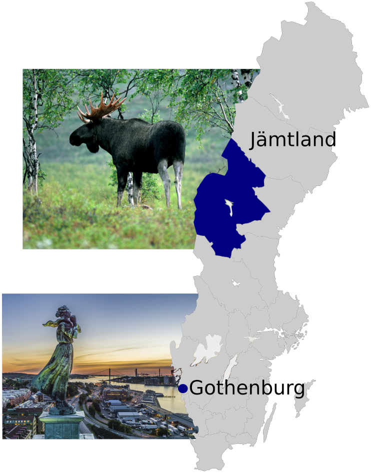
Map



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Sickness Insurance System During the Experiment

Somewhat more generous than current system, but similar in many respects

- Most workers received 90% income replacement rates (80% today)
- All reimbursements from government-run insurance funds (employer responsible for the first 14 days today)
- Coverage from first day of absence (no "qualification day"/karensdag) - but focus on spells of durations where this is unlikely to be a factor
- Monitoring by doctors after seven days of absence - like today
- Leave for taking care of sick children (VAB) - similar monitoring and replacement rates, unaffected by experiment
- Similar provisions are in place in many European countries today (Palme and Persson, 2020)

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Determinants of Sickness Absence

A significant number of factors have been identified as potentially connected to sickness absence in the literature

- Gender and income (Hartman, Hesselius and Johansson, 2013)
- Previous health history (Avdic and Johansson 2013)
- Family situation (Barmby et al. 2002)
- Education (Johansson and Nilsson 2008)
- Work environment/peers (Hesselius, Johansson, Vikström, 2008, Johansson, Karimi, Nilsson 2014)
- Plant characteristics (Winkelmann 1999), key position at plant (Hensvik and Rosenqvist 2015), tenure (Bratberg and Monstad, 2015)
- Public or private sector, industry (Barmby et al., 2002, Frick and Malo, 2008)

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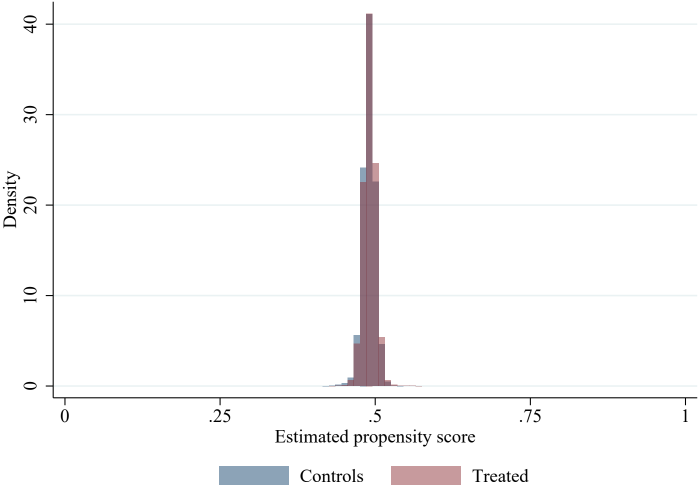
Propensity Scores Among Treated and Controls



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GRF setup

Clustering: on the family level

Training set: 80 percent sample of families

Held-out test set: 20 percent of families

Number of trees = 5000

Main specification: tuned parameters

- Minimum node size=1, maximum imbalance=0.034, imbalance penalty=1.4, N variables sampled=21 instead of 28, sample fraction=0.44, honesty fraction=0.71
- Default GRF parameters give similar results

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Best Linear Predictor Test

Tests how well the forest's estimates fit the actual duration of spells

	Estimate	Std. Error
α	1.01	0.002
β	1.28	0.018

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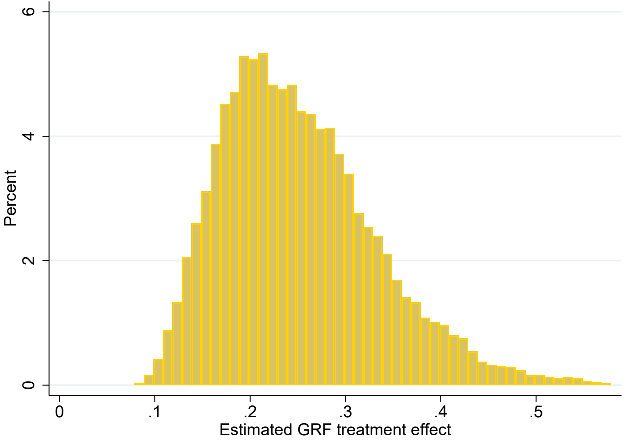
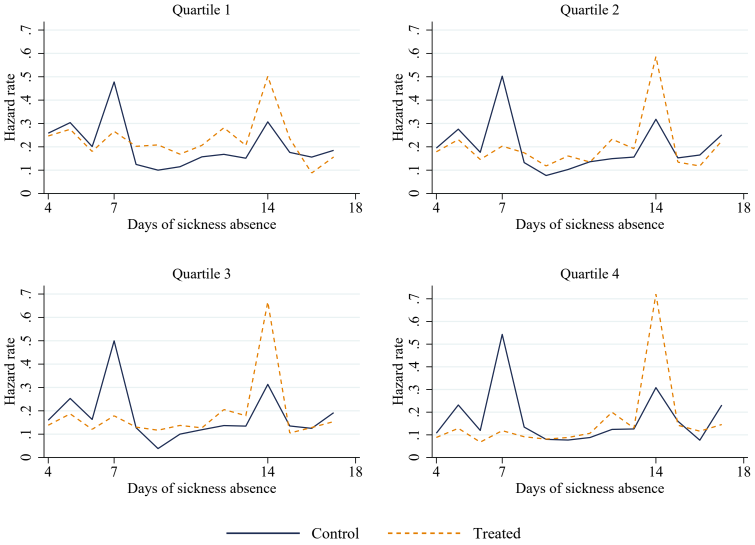
Probability of Returning to Work in Week 2: Treatment Effect Estimates



Correlation with duration estimates: 0.90 Back

Hazard Rates by Predicted Treatment Effects



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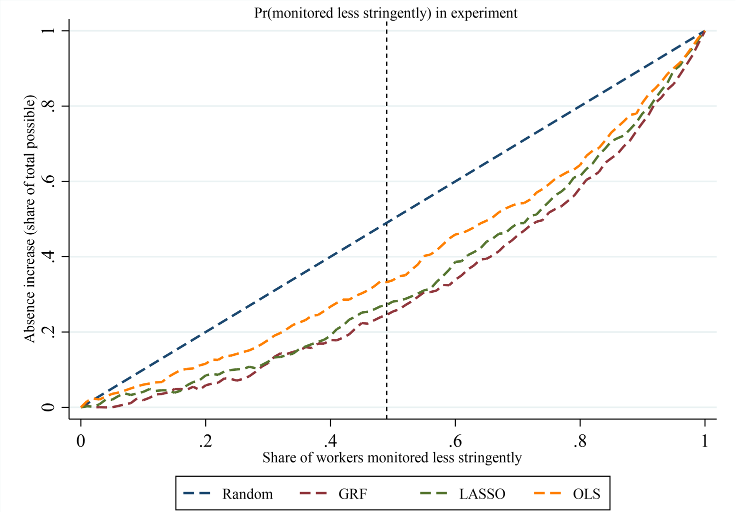
Targeted Monitoring Policy: Comparison to OLS and LASSO



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QINI Coefficients of Different Targeting Policies

	QINI	Std. Error
Full GRF	0.202	0.015
Sickness absence history	0.092	0.015
Social payment income share	0.093	0.014

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