

# Friday Morning Fever. Evidence from a randomized experiment on Sickness Leave Monitoring in the Public Sector

CRES-UPF, Barcelona

Tito Boeri <sup>1</sup>   Edoardo Di Porto <sup>2</sup>   Paolo Naticchioni <sup>3</sup>  
Vincenzo Scrutinio <sup>4</sup>

<sup>1</sup> Bocconi University, LSE , IZA

<sup>2</sup>CSEF, INPS, University of Naples Federico II

<sup>3</sup>INPS, IZA, University Roma Tre

<sup>4</sup>IZA, LSE, University of Bologna

November, 2023



## Introduction: Sick leave

- Paid sick leave is a key institution protecting workers' health and providing income smoothing when they are hit by a negative health shock.
- The scope of sickness benefits has been considerably enhanced during the pandemic to reduce presenteeism and the risk of contagion
- These schemes currently absorb more than 1% of GDP in OECD countries.
- The design of sickness benefits poses problems of moral hazard.

# Moral Hazard

- According to the European Working Conditions Survey (EWCS), public employees stay at home for illness reasons (over a one-year span) 1.5 days more than their counterparts in the private sector (24%-64% in the Mediterranean Countries);
- The higher incidence of sick pay in the public sector cannot be explained by differences in the characteristics of the 2 samples
- Governments typically deal with moral hazard problems by adjusting the level and coverage of sickness benefits. However, the fine-tuning is difficult due to heterogenous preferences and health conditions.
- Effective enforcement can be a better tool to deal with moral hazard without encouraging presenteeism than cuts in the level and duration of benefits

# Moral Hazard: an example

**TGCOM 24** MEDIASET Martedì 14 Novembre

Tgcom24 | Cronaca

10 SETTEMBRE 2021 17:28

## Atac, si dà malata per un anno e mezzo e intanto gestisce un B&B alle Canarie

A tradire la 50enne è stata la voglia di mostrare sui social la nuova vita. L'Inps ha aperto un'indagine e ora rischia il licenziamento

[f](#) [x](#) [whatsapp](#) [reply](#) [share](#) [in](#) [mail](#) [print](#) [LEGGI DOPO](#) [COMMENTA](#)

(8.1K)



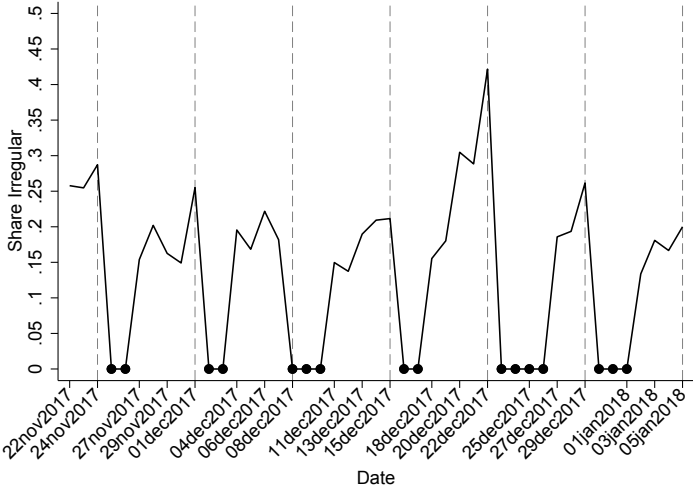
## Brief history of sick leave monitoring in Italy

- In 2010 the government decides to centralize Home Visits (HV) for **private employees** the duty passes from local health agencies to INPS.
- In 2011 INPS hires *fiscal* doctors (GP) and builds a digital infrastructure called *Savio* to manage centralized HV program.
- In 2017 the government decides to centralize HV for **public employees** the duty pass from local health agencies to INPS.
- INPS decides to start the new duty with an RCT, our RCT!

# This Paper: what do we do?

- We planned, performed, and analyzed a population-wide randomized control trial, run between November 22, 2017 and January 5, 2018. We randomly assign Home Visits (audits) to public sector workers on sick leave.
- Focus on the **public sector**:
  - Lower role for performance.
  - Protected sector.
  - Provide important public services (health, justice, education)
- Italy ideal case study: high level of absenteeism; evidence of strategic behavior; many similarities with other countries. [Table](#) [Graphs](#)
- **Data**: administrative data from the social security on workers' sick leave use and careers.

# Friday morning (or pre-holiday) fever



# This Paper: preview of the results

- Impact of HV:
  - -3.59 days of sick leave over 16 months (-8.3% of control group);
  - Less certificates in short term and shorter duration in short and long run;
  - No effect on relapse (*no presenteeism*);
  - No effects on workers' career; no evidence of program substitutions (retirement or disability).
- Descriptive: stronger reactions for workers found irregularly on leave and negative impact on career.
- Back of the envelope: 6.2 Euro saved per 1 Euro spent (5.2 net savings). We do not account for spillovers (lower bound).
- We do not find sizable differences of the deterrence effect along the income distribution: this implies lower MVPF for HV on top incomes.



# Literature review

- **Sick Leave changes:** Markussen et al. (2011) Godoy-Olsen (2018) Hernaes (2018) on Norway; Engstrom and Johansson (2012) and Bockerman et al. (2018) on Finland; D'Amuri (2011) in Italy. Marie, O. and Vall Castelló, J. (2022) on Spain. **Enforcement:** Hesselius (2005, 2009 and 2013) in Sweden. **Presenteeism:** Pichler and Ziebarth (2017)

## **Contribution:**

- Focus on enforcement; Impact on public sector: crucial component of the economy; Population level experiment; Connection to careers.
- **Enforcement** (tax collection): Kleven et al. (2011), De Neve et al. (2020), Bergeron et a. (2020).  
**Contribution:**
  - Randomized “audit” in sick leave setting. Largely unexplored.

- **MVPF:** Boening et al. (2023)

## **Contribution:**

- Extension on sick leave audits

## Institutional setting: sick leave rules

- Workers go to GP who certifies disease and writes certificate. Certificate then transmitted to employer and social security.
- Duration: 18 months with benefits + 18 with no benefit over 4 years
- Generosity:
  - First 10 days: 100% base wage (no allowances or other additional components of wage).
  - From 11th day to 9th month: 100% of wage from collective agreement.
  - From 10th to 12th month: 90% of wage from collective agreement.
  - From 13th to 18th month: 50% of wage from collective agreement.
- Surgeries, day hospital and treatments for chronic disease exempted from the reductions
- During period of sick leave, workers may receive home visits from INPS doctors.

## Institutional setting: monitoring

- Before November 2017, INPS was carrying out own HVs limited to private sector employees.
- Since November 2017, INPS performed Home Visit (HV) monitoring for private and public sector employees.
- HVs verify whether the sick leave reported information matches the true health conditions of worker.
- There are no automatic sanction if worker found irregularly on leave. Employers in charge to determine the sanction (up to dismissal).

## Selection for HV: Savio

HV visits for private employees based on algorithm (SAVIO). Procedure involves several steps:

- 1 Algorithm selects a random sample of ongoing certificates.
- 2 Algorithm excludes exempt (e.g. cancer) certificates.
- 3 Among the non-exempt, a second random sample is drawn and a ranking is determined, based on machine learning procedure determines the order of the HV. The aim is to maximize detection of irregularities.
- 4 Matching of visits to doctors to minimize costs. Doctors implement visit based on ranking

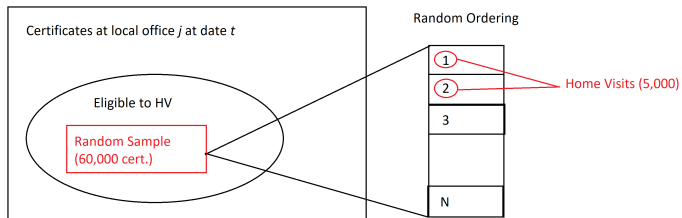
# Experimental Design

- We act on the third step of the HV assignment procedure by randomizing the priority order of certificates for HV.
- Randomized visits took place between 22nd of November 2017 and 5th of January 2018.
- About 4,300 visits performed and sample covers about 43,000 employees (treated and controls).
- Under Savio, full compliance of doctors with the rule. No change in the practice under the experiment.
- Doctors not aware of the change in the procedure: behaviour not affected by the experiment (no *Hawthorne effect*).

# Home Visits and The Experiment

- During the HV, doctors check the health status of the worker and report to the the social security and the employer.
- They are *administrative* doctors they cannot provide drugs.
- We cannot exclude that they can give advice on health issues.
- We analyze relapses to understand possible effects on home visit induced presenteeism

# Experimental Design



# Data

Record linkage of three administrative sources, released by INPS:

- 1 A dataset containing all the certificates sent to Inps from 2016 to September 2019 for the public sector.
- 2 A dataset containing all the HV visits made by Inps since 2017 including the randomized visits.
- 3 A brand new dataset that we use for the first time called POS.PA on Italian public employees containing precise information on employment and wages at monthly level from 2016 to 2019.

We restrict the sample to workers present at least once in the public sector data between May and November 2017 .



# Summary statistics: Individuals

Variables	Average	Se	Minimum	Median	Max
Female	0.725	0.446	0	1	1
Age	53.366	8.473	24	55	67
North	0.396	0.489	0	0	1
Center	0.177	0.382	0	0	1
South	0.427	0.495	0	0	1
School and University	0.396	0.489	0	0	1
Central Administration	0.060	0.238	0	0	1
Local Administration	0.234	0.423	0	0	1
Health Sector	0.310	0.463	0	0	1
Permanent Contract	0.948	0.222	0	1	1
Part Time	0.060	0.238	0	0	1
(log) Mean Monthly Earnings	7.605	0.737	0	8	10
Days on sick leave in following 16 months	45.019	65.556	0	20	483
Certificates in following 16 months	6.083	7.435	0	4	190
Average Certificate duration in following 16 months	6.980	8.457	0	4	92
Number of Certificates (bef. exp.)	2.719	3.156	0	2	59
Number of Days (bef. exp.)	23.376	34.041	0	9	184
Mean Duration Certificate (bef. exp.)	8.388	10.439	0	5	93
Duration First Certificate	14.43	12.60	3	10	93
Days In Experiment	13.043	12.036	1	8	45
Home Visits and outcome: individual					
Individual subject to Home Visit	0.098	0.297	0	0	1
Outcome Home Visit: Regular	0.078	0.268	0	0	1
Outcome Home Visit: Irregular	0.020	0.140	0	0	1
Home Visits and outcome: certificate					
Certificates subject to Home Visit	0.080	0.271	0	0	1
Outcome Home Visit: Regular	0.064	0.245	0	0	1
Outcome Home Visit: Irregular	0.016	0.125	0	0	1
# Workers	42,707				

# Empirical strategy

- Regression at individual level;

$$\#DaysOnSickness_{ij} = \alpha + \beta Visited_{ij} + X_{ij}\gamma + D_i + \theta_j + \varepsilon_{ij} \quad (1)$$

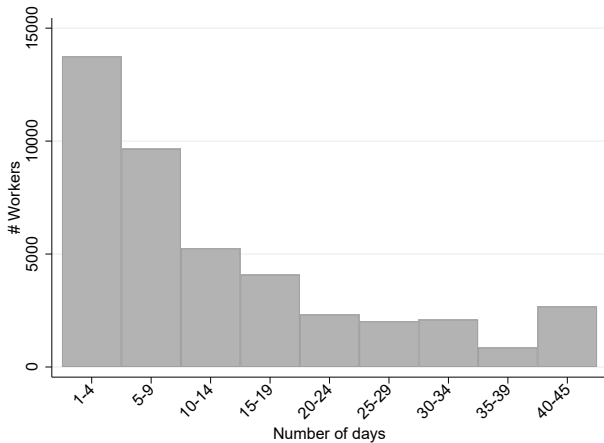
- Controls include ( $X_{ij}$ ):
  - Demographics characteristics.
  - Job characteristics.
  - Sickness leave in the six months before experiment (number of certificates, days on sickness leave, average leave duration)
- $D_i$ : fixed effects for time spent on leave in the experiment period by worker  $i$ .
- $\theta_j$  is a fixed effect at local office level.
- Standard errors clustered at local office level.

## *Caveat* in the empirical strategy

- Main issues:
  - **Caveat:** Individuals eligible as far as they remain in the sample in the period of the experiment (long certificates, multiple certificates)
    - Simple Solution: Include  $D_i$  i.e. fixed effect for number of days on leave in the period of experiment.
  - However, it can still be argued that time spent on leave in the experiment might be affected by unobserved factors (i.e. individual specific health conditions)

# Individuals by number of of days in period of experiment

Certificates



# Balancing: Normalized differences at individual level

Balancing Reg

Variable Name	Average (treated)	Average (control)	Normalized Difference
Female	0.740	0.724	0.037
Age	54.111	53.285	0.098
School Sector	0.447	0.391	0.114
Central Administration	0.066	0.059	0.029
Local Administration	0.196	0.238	-0.102
Health Sector	0.291	0.312	-0.046
Permanent Contract	0.968	0.946	0.108
Part Time	0.049	0.062	-0.054
Manager	0.037	0.028	0.053
(Log) Average Wage (six month bef. exp)	7.606	7.605	0.001
Metropolis	0.103	0.120	-0.055
Days on Leave in Experiment	25.132	11.730	1.108
Total certificates (6 months bef.)	3.643	2.618	0.326
Total number of days (6 months bef.)	42.663	21.281	0.564
Average duration cert. (6 months bef.)	15.015	7.669	0.640
Duration first certificate	25.302	13.252	0.934
P-value joint test			0.000

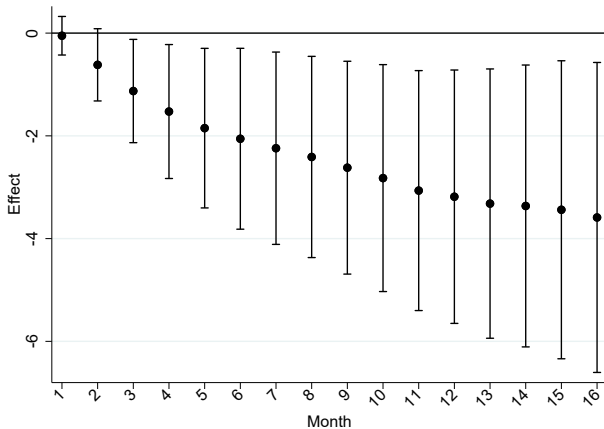
## Days on sickness leave: Over 16 months

Table

Relapse

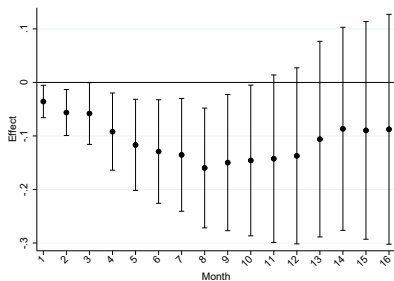
VARIABLES	(1)	(2)	(3)	(4)	(5)
	#Days in 16 months	#Days in 16 months	#Days in 16 months	#Days in 16 months	#Days in 16 months
HV	17.187*** (1.679)	12.285*** (1.788)	-2.318 (1.796)	-3.852** (1.550)	-3.589** (1.539)
Total certificates (6 months bef.)				4.981*** (0.172)	5.010*** (0.170)
Total number of days (6 months bef.)				0.200*** (0.026)	0.197*** (0.025)
Average duration cert. (6 months bef.)				-0.271*** (0.054)	-0.304*** (0.053)
Duration first certificate				0.353*** (0.053)	0.343*** (0.052)
Observations	42,707	42,704	42,704	42,704	42,657
R-squared	0.006	0.030	0.066	0.152	0.162
Mean Dep	43.335	43.335	43.335	43.335	43.335
Sede FE	NO	YES	YES	YES	YES
Days in the Experiment FE	NO	NO	YES	YES	YES
Past Cert.	NO	NO	NO	YES	YES
Controls	NO	NO	NO	NO	YES

# Number of days on sickness leave: Dynamic

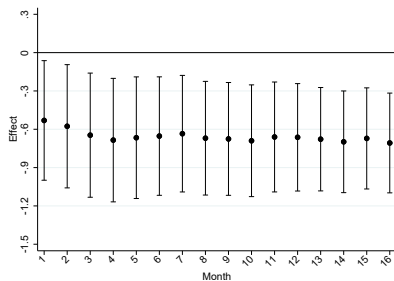


# Decomposing: Extensive and Intensive Margin

Table



**Figure:** Cumulative Certificates



**Figure:** Avg. Duration Certificate



# Heterogeneity

- Stronger impact on older workers. [Graph](#)
- No differences between men and women. [Graph](#)
- Stronger impact in the South and Centre of Italy. [Graph](#)
- Stronger effect in Central Administration and in the Health sector; no impact in the School sector and in Local Administrations. [Graph](#)

# Robustness

- Stratified estimation [Graph](#)
- Randomized inference [Graph](#)
- Exogenous certificate duration (1 certificate, within experiment) [Table](#)
- IV exposure to the experiment [Table](#)
- Workers present for 16 months [Table](#)
- Multiple Hypothesis testing [Table](#)
- Role of unobserved heterogeneity (Oster) [Table](#)

# An alternative strategy

- We can assume that unobserved factors are time invariant and rely on randomization and individual fixed effect for the causal identification.
- A difference in difference (DiD) strategy has two main advantages:
  - 1 if individual health conditions can be considered a time invariant factor, DiD resolves our main *Caveat*
  - 2 if misusing paid sick leave can be considered a time invariant factor, DiD allows to identify the effect of irregular(or regular) outcome of the visit on future outcomes.

# Difference-in-Difference

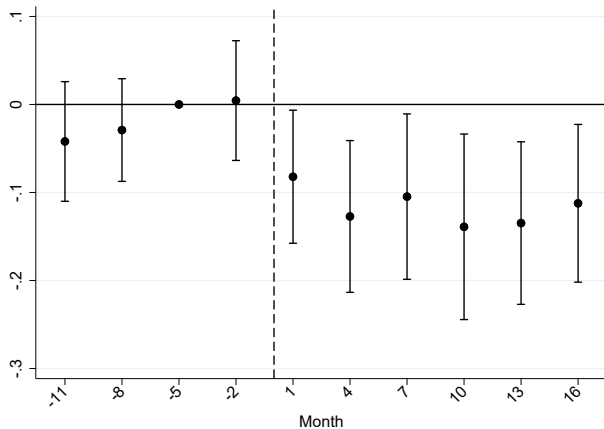
- Regression at individual level;

$$\begin{aligned}
 Y_{ijt} = & \alpha + \sum_{l \in \{-12, -11, \dots, 18\} / \{-1\}} \beta_l I(t - t_e = l) XHV_i + \\
 & + \sum_{l \in \{-12, -11, \dots, 18\} / \{-1\}} \gamma_l I(t - t_e = l) XD_i + \\
 & + \sum_{l \in \{-12, -11, \dots, 18\} / \{-1\}} \gamma_l I(t - t_e = l) XSede_j + \delta_i + \lambda_t + \varepsilon_{it} \quad (2)
 \end{aligned}$$

- $Y_{ijt}$  outcome for individual  $i$  at time  $t$  and at INPS local office  $j$ .
- $D_i$ : fixed effects for time spent on leave in the experiment period by worker  $i$ .
- $\delta_i$  individual fixed effects and  $\lambda_t$  month fixed effect.

# Difference-in-Differences: Days

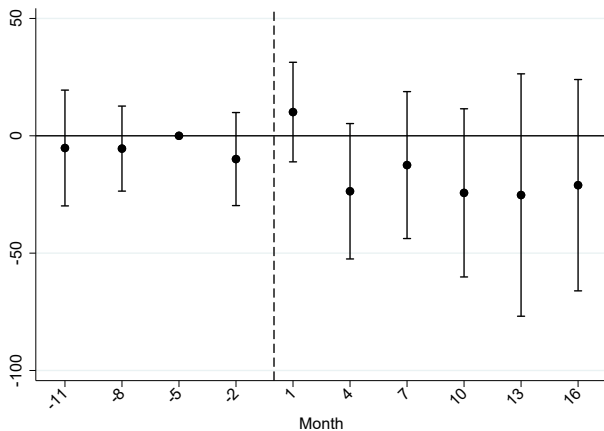
no Exp



## Difference-in-Differences: Salary

Work

Prom



# Regular vs Irregular: Days and Career Promotions

extensive Char Work Prom Model

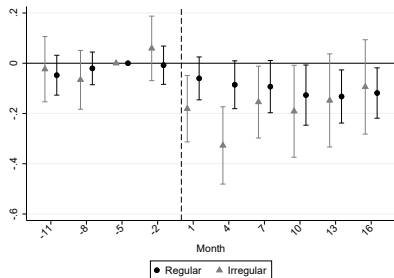


Figure: Days

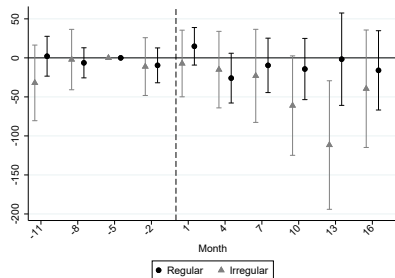


Figure: Salary

## CBA: back of the envelope

- Net costs of inspections for the taxpayer. A *random* visit reduces days on sickness leave by about 3.6 days over 16 months.
- Net gain per Euro spent:

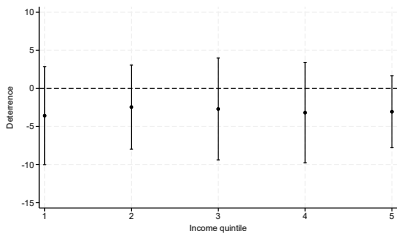
$$NG = \frac{\beta * \frac{\tilde{w}}{\text{DayMonth}} - \text{Cost}}{\text{Cost}} = \frac{3.6 * 86.3 - 50}{50} = 5.2$$

- Targeting Irregular with Machine Learning (Savio; 40% detection rate instead of 20%): 6.6 Euro of net savings.
- Utility cost of lowering expenditure:

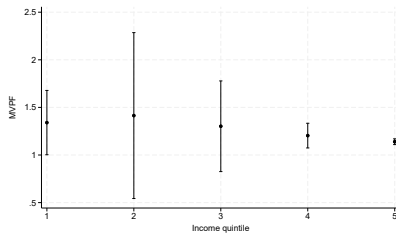
$$MVPF = \frac{-6.2}{-5.2} = 1.2$$



# MVPF by wage quintile



**Figure: Deterrence Effect**



**Figure: MVPF**

# MVPF by wage quintile

Earning Quintile	(1) Deterrence	(2) Daily Wage	(3) Benefit Expenditure decline	(4) MVPF
1	-3.588	54.846	-196.788	1.341
2	-2.46	69.384	-170.686	1.414
3	-2.705	79.692	-215.568	1.302
4	-3.187	92.615	-295.165	1.203
5	-3.061	133.269	-407.937	1.14

# Conclusions

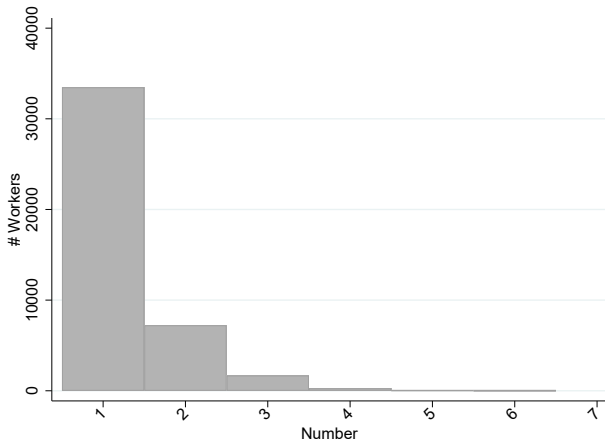
- Absenteeism is an important issue in the public sector across the world.
- Very little evidence on the role of monitoring.
- Exploit unique experiment randomizing HV for public sector workers
- HV effective in reducing use of sickness leave
  - Decline by 8% in sick leave use, mostly at intensive margin.
  - No evidence of adverse health effects.
  - No impact on average workers' career
  - Descriptive evidence of larger changes in behavior for workers found irregularly on leave and worse career.
  - Extremely cost effective
- Tool useful to reduce moral hazard in the use of sick leave.

# THANKS!

# Appendix

# Individuals by number of of certificates in period of experiment

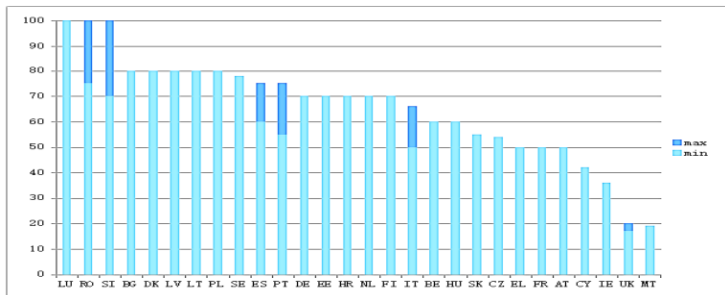
Main



# Comparison of Sickness Leave Benefits (I) Main

Country	Replacement Rate	Duration
United States	0	0
United Kingdom	16	28
Greece	19	104
Australia	19	520
New Zealand	20	520
Malta	21	52
Ireland	29	104
Slovak Republic	42	52
France	49	52
Italy	50	26
Denmark	51	22
Czech Republic	53	54
Cyprus	55	52
Canada	55	15
Portugal	55	156
Spain	60	52
Japan	66	78
Estonia	69	26
Hungary	69	52
Bulgaria	70	520
Netherlands	70	104
Romania	75	26
Latvia	78	26
Lithuania	79	520
Slovenia	80	520
Poland	80	26
Sweden	80	52
Austria	100	78
Luxembourg	100	52
Finland	100	50
Switzerland	100	11
Germany	100	78
Belgium	100	52
Norway	100	52

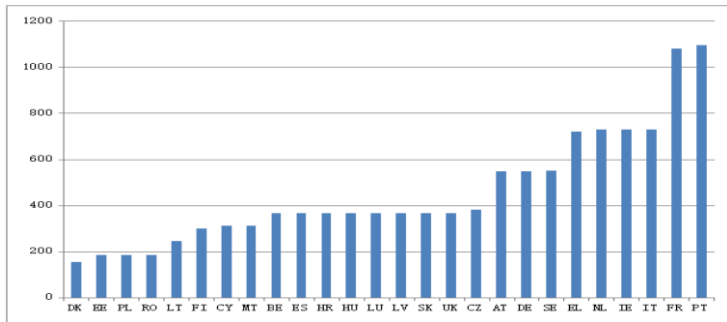
# Comparison of Sickness Leave Benefits (II) Main



(a) Replacement Rate



# Comparison of Sickness Leave Benefits (III) Main



(b) Duration

# Balancing regression: Individual Main

VARIABLES	(1) Visit	(2) Visit	(3) Visit	(4) Visit
Female	0.006* (0.003)	0.006* (0.003)	0.009*** (0.003)	0.009*** (0.003)
Age: 36-40	0.007 (0.009)	0.001 (0.009)	-0.001 (0.009)	-0.002 (0.009)
Age: 41-45	0.009 (0.008)	0.005 (0.007)	0.001 (0.007)	0.000 (0.007)
Age: 46-50	0.012 (0.009)	0.005 (0.008)	-0.001 (0.008)	-0.002 (0.007)
Age: 51-55	0.007 (0.008)	0.002 (0.007)	-0.006 (0.007)	-0.008 (0.006)
Age: 56-60	0.009 (0.009)	0.003 (0.008)	-0.010 (0.007)	-0.012 (0.007)
Age: 61-65	0.021** (0.010)	0.015* (0.008)	-0.004 (0.008)	-0.007 (0.008)
Age: 66-67	0.076*** (0.014)	0.060*** (0.013)	0.039*** (0.011)	0.036*** (0.011)
Permanent	0.034*** (0.006)	0.025*** (0.005)	0.005 (0.005)	0.003 (0.005)
Part Time	-0.001 (0.007)	-0.002 (0.006)	-0.005 (0.006)	-0.005 (0.006)
(log) Mean Monthly Earnings	-0.001 (0.002)	-0.001 (0.002)	0.000 (0.002)	0.000 (0.002)
Central Admin.	-0.002 (0.009)	-0.006 (0.008)	-0.000 (0.007)	-0.001 (0.007)
Local Admin.	-0.026*** (0.006)	-0.017*** (0.004)	-0.000 (0.004)	0.000 (0.004)
Health Sector	-0.017*** (0.005)	-0.013*** (0.004)	-0.004 (0.004)	-0.004 (0.004)
Number of Certificates (bef. exp.)				0.000 (0.001)
Number of Days (bef. exp.)				0.000 (0.000)
Mean Duration Certificate (bef. exp.)				0.001*** (0.000)
Observations	42,660	42,657	42,657	42,657
R-squared	0.004	0.088	0.183	0.184
P-value joint sig.	0.000	0.000	0.000	0.000
Mean Dep	.098	.098	.098	.098
Sede FE	NO	YES	YES	YES
Days in Experiment FE	NO	NO	YES	YES

# Table for main results: Effect of Visit Main

VARIABLES	(1)	(2)	(3)	(4)	(5)
	#Days in 16 months	#Days in 16 months	#Days in 16 months	#Days in 16 months	#Days in 16 months
HV	17.187*** (1.679)	12.285*** (1.788)	-2.318 (1.796)	-3.852** (1.550)	-3.589** (1.539)
Total certificates (6 months bef.)				4.981*** (0.172)	5.010*** (0.170)
Total number of days (6 months bef.)				0.200*** (0.026)	0.197*** (0.025)
Average duration cert. (6 months bef.)				-0.271*** (0.054)	-0.304*** (0.053)
Duration first certificate				0.353*** (0.053)	0.343*** (0.052)
Female					0.217 (0.826)
Age: 36-40					2.199 (1.444)
Age: 41-45					5.156*** (1.385)
Age: 46-50					5.094*** (1.418)
Age: 51-55					7.620*** (1.469)
Age: 56-60					9.830*** (1.420)
Age: 61-65					16.153*** (1.562)
Age: 66-70					-3.051 (2.506)
Central Administration					-13.560*** (1.565)
Local Administration					-9.004*** (1.038)
Health					-5.108*** (0.952)
Permanent Contract					6.234*** (1.196)
Part Time					2.321* (1.248)
Manager					-10.628*** (1.539)
(Log) Average Wage (six month bef. exp)					-1.822*** (0.445)
Observations	42,707	42,704	42,704	42,704	42,657
R-squared	0.006	0.030	0.066	0.152	0.162
Mean Dep	43.335	43.335	43.335	43.335	43.335
N. obs	42707	42707	42707	42707	42707
Sede FE	NO	YES	YES	YES	YES
Days in the Experiment FE	NO	NO	YES	YES	YES
Past Cert.	NO	NO	NO	YES	YES
Controls	NO	NO	NO	NO	YES

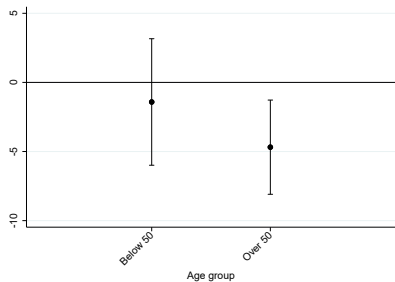
# HV and Relapses Main

VARIABLES	(1) #Cert: Renewal	(2) #Cert: No Renewal	(3) #Days: Renewal	(4) #Days: No Renewal
HV	-0.049 (0.032)	-0.038 (0.101)	-1.371** (0.655)	-2.218* (1.217)
Observations	42,657	42,657	42,657	42,657
R-squared	0.109	0.401	0.076	0.148
Mean Dep	0.611	5.465	7.743	35.592
Controls	YES	YES	YES	YES
Past Cert.	YES	YES	YES	YES
Sede FE	YES	YES	YES	YES
Days in the Experiment FE	YES	YES	YES	YES

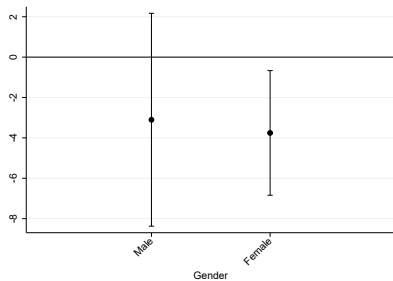
# Table for main results: Effect of Visit Main

VARIABLES	(1) #Days in 16 months	(2) #Cert. in 16 months	(3) Mean Days in 16 months	(4) Mean Days in 16 months
HV	-3.589** (1.539)	-0.088 (0.110)	-0.707*** (0.199)	-0.935*** (0.204)
Observations	42,657	42,657	42,657	36,883
R-squared	0.162	0.410	0.195	0.265
Mean Dep	43.335	6.076	6.686	7.739
N. obs	42707	42707	42707	36925
Controls	YES	YES	YES	YES
Past Cert.	YES	YES	YES	YES
Sede FE	YES	YES	YES	YES
Days in the Experiment FE	YES	YES	YES	YES

# Heterogeneity: Age & Gender Main

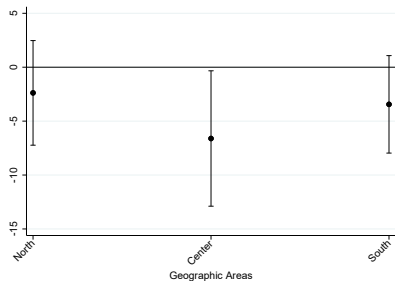


**Figure: Age**

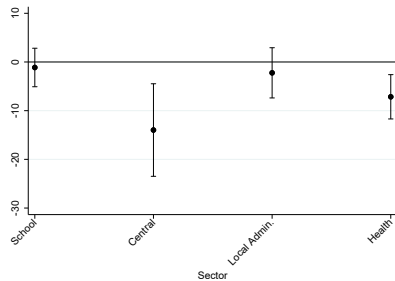


**Figure: Gender**

# Heterogeneity: Geography & Sector Main

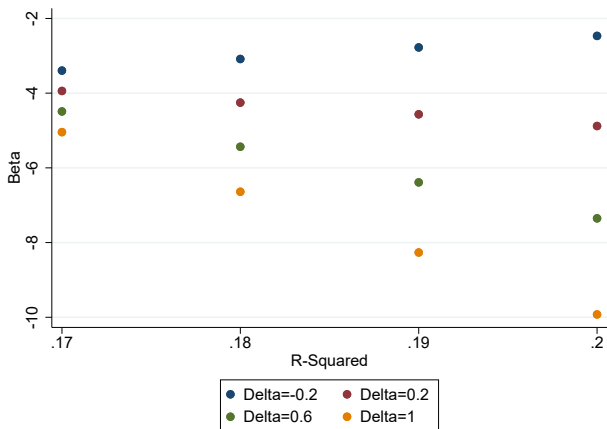


**Figure: Geography**



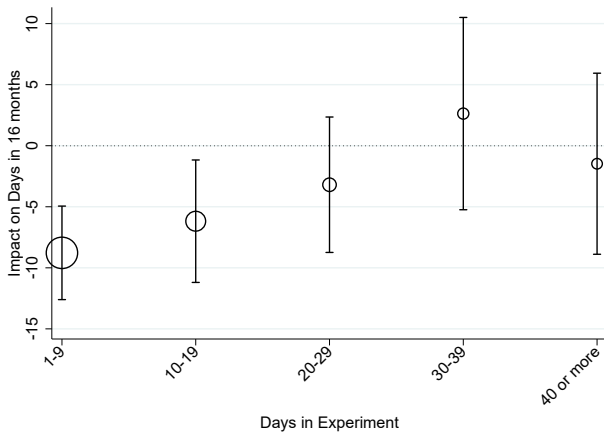
**Figure: Sector**

# Unobserved Heterogeneity: Oster (2019) Main

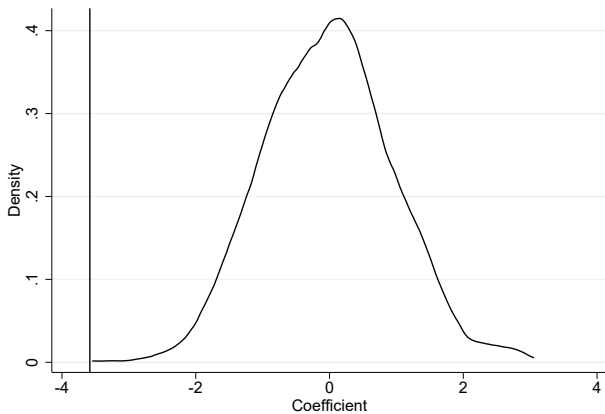




# Stratified Estimation Main



# Randomized inference Main



Note: Share of coefs above main coefficient is 1

# Multiple Hypothesis Testing Main

Outcome	(1) Baseline	(2) Coef	(3) Remark 3.2	(4) Thm 3.1	(5) Remark 3.8	(6) Bonf.	(7) Holm.
Days in 16 months	-3.32	-5.59	0.002	0.003	0.003	.005	0.003
Certificates in 16 months	-0.102	-0.39	0.013	0.013	0.013	0.040	0.013
Average Days per Certificate	-0.576	-0.90	0.000	0.000	0.000	0.001	0.001

# Workers present for 16 months Table

VARIABLES	(1) #Days in 16 months	(2) #Cert. in 16 months	(3) Mean Days in 16 months	(4) Mean Days in 16 months
HV	-4.829*** (1.763)	-0.197 (0.132)	-0.836*** (0.196)	-0.995*** (0.198)
Observations	33,430	33,430	33,430	29,318
R-squared	0.162	0.455	0.152	0.196
Mean Dep	41.532	6.248	6.171	7.043
N. obs	33450	33450	33450	36925
Controls	YES	YES	YES	YES
Past Cert.	YES	YES	YES	YES
Sede FE	YES	YES	YES	YES
Days in the Experiment FE	YES	YES	YES	YES

# Exogenous certificate duration Table

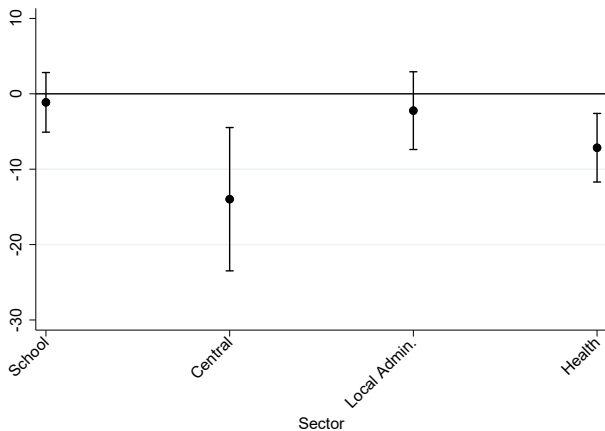
VARIABLES	(1)	(2)	(3)	(4)	(5)
	#Days in 16 months	#Days in 16 months	#Days in 16 months	#Days in 16 months	#Days in 16 months
HV	12.375*** (2.546)	3.762 (2.715)	-3.433 (2.841)	-4.400 (2.762)	-4.064 (2.740)
Observations	18,727	18,725	18,722	18,722	18,697
R-squared	0.002	0.034	0.050	0.172	0.183
Mean Dep	43.335	43.335	43.335	43.335	43.335
N. obs	42707	42707	42707	42707	42707
Controls	NO	NO	NO	NO	YES
Past Cert.	NO	NO	NO	YES	YES
Sede FE	NO	YES	YES	YES	YES
Days in the Experiment FE	NO	NO	YES	YES	YES

# Instrumental variable: exposure to the experiment

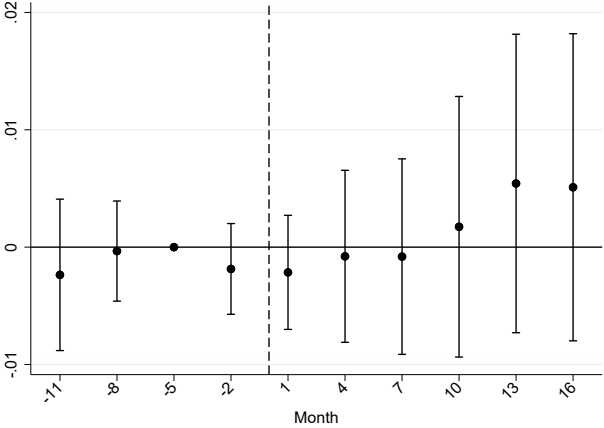
Table

VARIABLES	(1) Baseline	(2) Linear	(3) IV
HV	-3.589** (1.539)	-3.668** (1.540)	-3.407** (1.645)
Observations	42,657	42,657	42,657
R-squared	0.162	0.161	0.138
Mean Dep	43.335	43.335	43.335
Controls	YES	YES	YES
Past Cert.	YES	YES	YES
Sede FE	YES	YES	YES
Days in the Experiment FE	YES	NO	NO
Cragg-Donald F-test			12375.196

# Heterogeneity by sector Main



# Employment in the Public sector Main





# Promotions Main

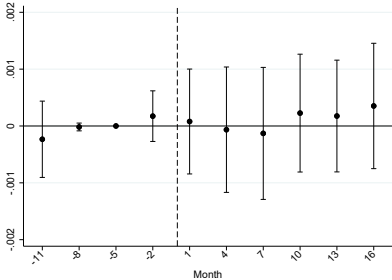


Figure: Manager

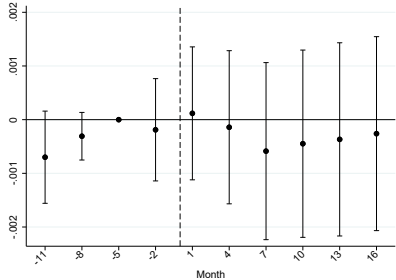
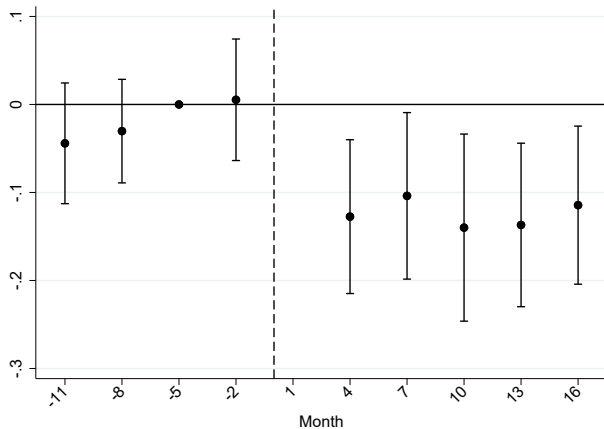


Figure: Occupation avg Pay

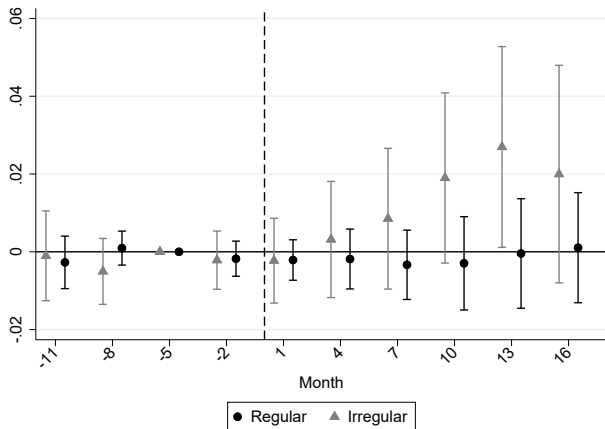
# Excluding period of the experiment Main



# Regular vs Irregular: Characterize Main

VARIABLES	(1)	(2)	(3)
	Irregular outcome	Irregular outcome	Irregular outcome
Female	-0.040** (0.019)	-0.046** (0.019)	-0.047** (0.019)
Age: 36-40	-0.025 (0.048)	-0.024 (0.048)	-0.020 (0.048)
Age: 41-45	-0.016 (0.049)	-0.014 (0.049)	-0.009 (0.049)
Age: 46-50	-0.050 (0.049)	-0.049 (0.049)	-0.046 (0.049)
Age: 51-55	-0.050 (0.047)	-0.050 (0.047)	-0.048 (0.047)
Age: 56-60	-0.032 (0.044)	-0.032 (0.044)	-0.030 (0.044)
Age: 61-65	-0.025 (0.046)	-0.018 (0.046)	-0.013 (0.046)
Age: 66-67	-0.017 (0.057)	-0.010 (0.058)	-0.002 (0.058)
Central Admin.	-0.077*** (0.024)	-0.081*** (0.024)	-0.077*** (0.024)
Local Admin.	-0.005 (0.017)	-0.013 (0.017)	-0.010 (0.017)
Health Sector	-0.036** (0.014)	-0.047*** (0.014)	-0.041*** (0.014)
Permanent	-0.099** (0.040)	-0.108** (0.039)	-0.113** (0.039)
Part Time	-0.040 (0.025)	-0.049** (0.025)	-0.052** (0.025)
Manager	-0.031 (0.024)	-0.029 (0.024)	-0.034 (0.024)
(log) Mean Monthly Earnings	0.002 (0.005)	0.002 (0.005)	0.001 (0.005)
Number of Certificates (bef. exp.)	0.001 (0.004)	0.002 (0.004)	0.001 (0.004)
Number of Days (bef. exp.)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Mean Duration Certificate (bef. exp.)	-0.001* (0.001)	-0.001** (0.001)	-0.001** (0.001)
Metropolis	0.061** (0.028)	0.044 (0.029)	0.031 (0.029)
Durata: 1-4	0.543*** (0.059)	0.542*** (0.060)	0.537*** (0.062)
Durata: 5-7	0.213*** (0.041)	0.209*** (0.041)	0.201*** (0.041)
Durata: 8-9	0.082** (0.037)	0.079** (0.037)	0.079** (0.038)
Friday	0.057*** (0.017)	0.057*** (0.017)	
Center	0.002 (0.025)		
South	0.053** (0.021)		
Observations	4,388	4,388	4,388
R-squared	0.063	0.059	0.060
Mean Dep	.199	.199	.199
Stale FE	NO	YES	YES
Date FE	NO	NO	YES

# Employment in the Public sector Main



# Promotions Main

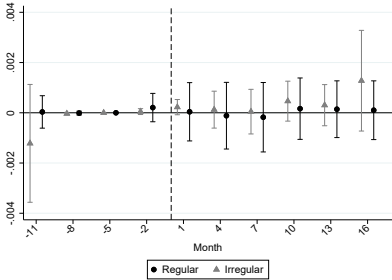


Figure: Manager

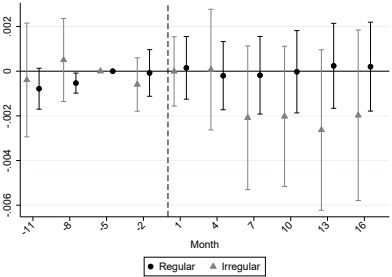


Figure: Occupation avg Pay

## Response without Automatic Sanctions Main

- In presence of risk aversion, uncertain sanction is a stronger deterrent than an automatic sanction
- Consider  $u(c, a) = c + a\Gamma$  with  $u' > 0$  and  $u'' < 0$  where  $a$  is absence: 1 if the worker is on leave (and healthy) and 0 otherwise.  $\Gamma$  is utility if worker can *get away with it*, and  $c$  is consumption
- A regular worker enjoys  $u(0) = w$
- A shirker expects  $u(1) = (1 - d)(w + \Gamma) + dw^l$  where  $w^l - w < 0$  is the wage sanction if detected
- If penalty is non-stochastic, it should be at least  $\frac{1-d}{d}\Gamma$  to be a deterrent.
- If mean preserving spread (penalty is 0,  $\frac{1-d}{d}\Gamma$  and  $\frac{2(1-d)}{d}\Gamma$  all with probability  $\frac{1}{3}$ ), then  $u(1) = \frac{1}{3}(2f(w) + f(w - \Gamma + d\Gamma))$ . Insofar as  $d < 1$  even a smaller penalty would convince the worker not to be irregularly absent.