THE HIDDEN COSTS OF MASS LAYOFFS

Do workers react with absenteeism when co-workers are fired?

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Motivation

Downsizing affects employees

- Downsizing can cause large layoffs (mass layoffs)
- impact on laid off employees
- impact on **survivors**
  Morrison & Robinson (1997), Datta et al. (2010), Goesaert et al. (2015)
  - survivor syndrome
    - distrust and frustration
    - fear of job loss
  - increased workload
- symptoms revealed by **survivors**
  - absenteeism
  - physical and psychological health problems (correlated with absenteeism)

Survivors determine future productivity of the firm

Defining the question

- Productivity of workers is not directly observed
- BUT: Absent workers cannot be productive
- Exploit absenteeism as proxy for productivity
    - number of sick leave (SL) days in one quarter
    - number of SL days including Mondays, Fridays, bridge days (possible shirking indicator)
    - doctors visits, psychiatric drug use/expenditures
- **mass layoff** event as structural change

Research Question

Do workers react with absenteeism when co-workers are fired?

Literature

- productivity after a ML
  - lower effort, performance and commitment
    Travaglione & Cross (2006), Goesaert et al. (2015), Drzensky & Heinz (2016), van Dick et al. (2016), Heinz et al. (2017)
  - absenteeism
    - increase in sickness absence (Vahtera et al. 2004)
    - increased absenteeism 36% (Travaglione & Cross 2006)
    - 2% decrease sick leaves (Osthus & Mastekaasa 2010)
    - no effect on absenteeism but 25% more likely to report going sick to work(Sigursteinsdottir & Rafnsdottirr 2015)
  - current shortcomings
    - low external validity
    - surveys (self reported) and small sample case studies
    - partial effect of anger, impact of end game effect

Contribution

- exploit registry data
  - overcome self-report response bias
  - increase sample size substantially
  - increase external validity
- examine understudied survivors
  - evaluate management decision of downsizing
  - outline potential productivity pit falls in survived workforce
  - examine implications for worker protection for survivors
- establish identification framework
  - minimize selection bias on firm level
  - use controls on firm and individual level
  - account for effect heterogeneity on individual characteristics

Data

- Austrian Social Security Database (ASSD) linked with Upper Austrian Health Insurance Fund data
- covers 75% of all Upper Austrians
- universe of all mass layoffs between 1996 and 2014
- drop groups of joint movers & exclude civil servants
- exclude farming, construction, mining & hospitality industry
- exclude firms with size smaller 20

Remark

Data preparation is still under development.
Cautious interpretation of preliminary results!

Mass layoffs

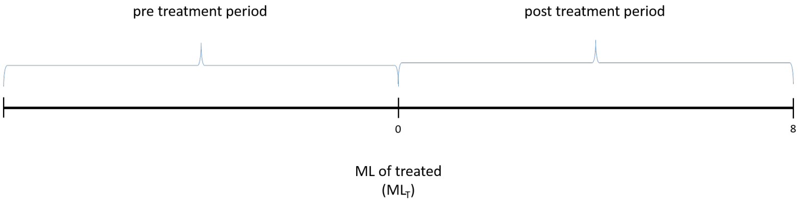
- **Definition of a mass layoff**

Firm size	laid off employees
$20 < \text{size} < 100$	at least five employees
$100 \leq \text{size} \leq 600$	at least five percent of employees
$600 < \text{size}$	at least 30 employees

Source: Public Employment Service Austria (AMS)

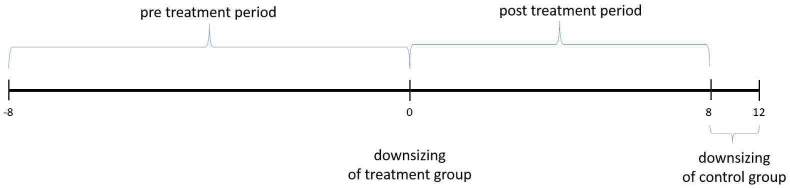
Treatment group

- **Treatment group restrictions**
  - the firm suffers a ML_T in time period t(0)
  - but did not suffer an earlier ML within eight quarters before ML_T (clean pre-treatment period)
  - and did not suffer a later ML eight quarters after ML_T (time horizon to analyse outcome)
  - it must exist throughout



Control group

- **Control group restrictions**
  - firm suffers a ML_C 8–12 quarters after treated firm $\rightarrow$ ML_C in time period t(8,12)
  - control firm did not suffer an earlier ML within 16–20 quarters before its own ML_C
  - firm did not suffer another ML eight quarters after the ML_C
- **Survivor restrictions**
  - constrain employees to ML_C survivors which were already working in t(-8,8)



Econometric methodology

The aim is to avoid selection bias and ensure causality

- Regression-adjusted semiparametric difference-in-difference matching
  Heckman et al. (1997), Marcus (2014), Chabe-Ferret (2015)
  - Matching (on firm level)
    - restrict control firms to firms with the "same" treatment probability as treated firms
    - apply radius matching to increase inference
      Huber et al. (2013, 2015)
  - Difference in Differences (DiD) (on individual level)
    - controls for constant unobserved group effects
    - individual level decreases standard errors

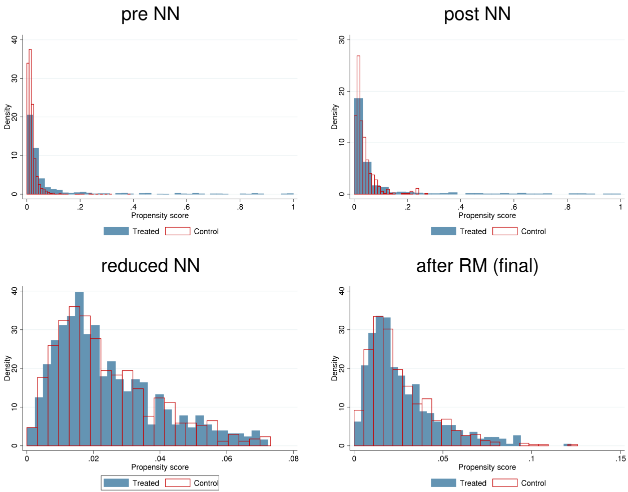
Identifying assumptions

- Matching
  - conditional independence assumption (CIA)
    - the ML probability is fully explained by observed variables
    - include many variables and lags (perfect and long data)
    - use future treated firms as controls
  - common support assumption (CSA)
    - apply truncation and radius matching
      Imbens (2004), Huber et al. (2013, 2015)
    - internal validity increases
- DiD
  - parallel trend assumption
  - mode of reporting sick leaves did not change over time

Matching method

1. Nearest neighbor (NN) propensity score matching (logistic regressions) on matching variables and entire pre treatment period t(-8,-1)
   - firm level: firm size, age, turnovers, tenure structures, wage share of employees with respect to working-class, education, age, and migration
   - nace3 level: share of market entries and leavers, unemployment rates, import and export growth
2. Truncate NN matches at 95th propensity score percentile of the treatment group
3. Radius matching
   - define radius as the 95th percentile of the absolute propensity score differences between T and C (common support)
   - All control firms within the radius of a treated firm are weighted proportional to the inverse of their distance to the treated firm and the weights are normalized to sum up to 1.

Propensity scores (stages of matching)



T-test of matching (pre-treatment)

Variable Names	Unmatched sample T	C	T-C	t-val		Matched sample T	C	T-C	t-val	
Firm characteristics										
Firm size	167.806	148.52	19.29	3.06	***	164.59	173.03	-8.44	1.26	
Formation	1979.551	1979.26	0.29	1.70		1979.43	1979.40	0.04	0.20	
Firm wage structure										
Average yearly wage	24979.402	25185.67	-206.27	1.08		24841.05	25395.77	-554.72	3.01	***
Sd of yearly wage	14248.549	14055.98	192.57	1.03		13934.30	14130.30	-196.00	1.27	
Firm quarterly fluctuations (share)										
New male employment	0.039	0.04	-0.00	0.83		0.04	0.04	-0.00	1.58	
New female employment	0.037	0.04	0.00	0.59		0.03	0.03	0.00	0.51	
New employment age< 25	0.022	0.02	-0.00	1.99	*	0.02	0.02	0.00	0.26	
New employment $25-50$	0.049	0.05	0.00	0.56		0.04	0.05	-0.00	0.57	
New employment > 50	0.005	0.01	-0.00	0.58		0.00	0.01	-0.00	1.83	
Male layoffs	0.030	0.03	-0.00	2.97	***	0.03	0.03	-0.00	1.95	
Female layoffs	0.027	0.03	-0.00	0.97		0.03	0.03	0.00	0.78	
Layoffs age< 25	0.014	0.02	-0.00	3.31	***	0.01	0.01	0.00	0.25	
Layoffs age$25-50$	0.037	0.04	-0.00	1.44		0.04	0.04	-0.00	1.19	
Layoffs age> 50	0.007	0.01	-0.00	1.35		0.01	0.01	-0.00	0.57	
Share of Employees by Education										
University degree	0.105	0.10	0.00	0.87		0.10	0.12	-0.02	5.46	***
High school degree	0.314	0.32	-0.00	1.19		0.31	0.32	-0.01	2.07	*
Apprenticeship examination	0.419	0.42	-0.01	1.85		0.42	0.41	0.01	3.98	***
Compulsory school	0.162	0.16	0.01	2.51	*	0.16	0.15	0.01	3.13	***
Share of employees by sex and age										
Female	0.454	0.45	0.01	1.42		0.46	0.45	0.01	1.71	
Male average age	38.248	38.21	0.04	0.35		38.32	38.32	0.00	0.04	
Female average age	37.673	37.62	0.05	0.55		37.82	37.62	0.21	2.00	*
Male and age $25-55$	0.431	0.43	0.00	0.42		0.43	0.43	-0.01	1.55	
Female and age $25-55$	0.364	0.35	0.01	2.38	*	0.37	0.36	0.01	1.43	
Share of employees by working class										
Female blue collar	0.152	0.15	0.00	1.15		0.16	0.15	0.01	3.27	***
Male blue collar	0.289	0.30	-0.01	1.27		0.29	0.29	0.00	0.75	
Female white collar	0.245	0.24	0.00	0.81		0.25	0.25	-0.01	1.23	
Male white collar	0.218	0.21	0.00	1.36		0.21	0.22	-0.01	2.29	*

Note: $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

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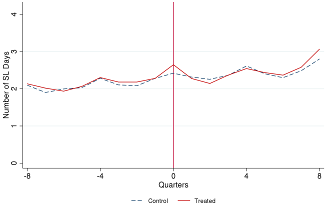
Estimation base

- matching on firm level completed
  - One treated firm can have several control firms.
  - Weighting is used to account for distance and higher number of firms in the control group
  - Essentially synthetic control groups
- Individuals are merged to firm data
  - DiD Estimations are performed on individual level

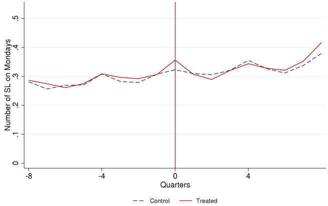
	Treated	Control
Mass layoffs	545	5,078
Unique Firms	442	488
Individuals	49,039	422,818
Unique Individuals	41,731	45,272

Parallel trends

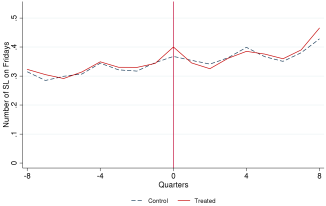
Number of SL days overall



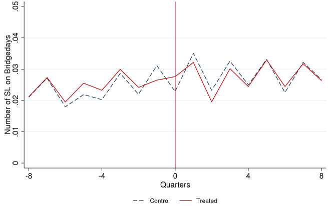
Number of SL days incl. Monday



Number of SL days incl. Friday



Number of SL incl. bridge days



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Estimation of DiD (on individual level)

(I) Basic model

$$Y_{ift} = \alpha + \gamma tg_f + \tau post_t + \delta tg_f * post_t + \varepsilon_{ift} \tag{1}$$

(II) add firm, individual control variables and industry fixed effects

$$\begin{aligned} Y_{ift} = {} & \alpha + \gamma tg_f + \tau post_t + +\delta tg_f * post_t \\ & + \beta F_{ft} + \kappa X_{ift} + \mathbf{I_f} + \varepsilon_{ift} \end{aligned} \tag{2}$$

(III) add trends

$$\begin{aligned} Y_{ift} = {} & \alpha + \gamma tg_f + \tau post_t + +\delta tg_f * post_t \\ & + \beta F_{ft} + \kappa X_{ift} + \mathbf{I_f} \\ & + \iota_0 trend_t + \varepsilon_{ift} \end{aligned} \tag{3}$$

(IV) add treatment group specific trends

$$\begin{aligned} Y_{ift} = {} & \alpha + \gamma tg_f + \tau post_t + \delta tg_f * post_t \\ & + \beta F_{ft} + \kappa X_{ift} + \mathbf{I_f} + \iota_0 trend_t \\ & + \iota_1 tg_f * trend_t + \varepsilon_{ift} \end{aligned} \tag{4}$$

Results - absenteeism

	(1)	(2)	(3)	(4)	Sample mean
Number of SL days overall	-0.0051	0.0018	-0.0071	-0.0105	2.2715
	(0.0539)	(0.0520)	(0.0542)	(0.0524)	(6.7178)
Number of SL days inkl. Monday	-0.0010	-0.0002	-0.0015	-0.0019	0.3067
	(0.0075)	(0.0072)	(0.0075)	(0.0072)	(0.9557)
Number of SL days inkl. Friday	-0.0017	-0.0005	-0.0022	-0.0026	0.3448
	(0.0077)	(0.0075)	(0.0078)	(0.0076)	(1.0080)
Number of SL inkl. bridge days	-0.0013	-0.0012	-0.0013	-0.0013	0.0258
	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.1847)
Single day SL on Mon/Fri and bridge days	-0.001	-0.0008	-0.0008	-0.0008	0.0073
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0927)
Individual level fixed effects	✓	✓	✓	✓	
Individual level controls		✓	✓	✓	
Firm level controls		✓	✓	✓	
Industry level fixed effects		✓	✓	✓	
Linear time trend			✓	✓	
Quarter specific cohort trends				✓	
Observations			8,158,793		

Note: Doctor visits, health spa stays, and sick leaves are measured in days per quarter. Psychiatric drug use is reported as 1 if they were consumed during a quarter and 0 otherwise. Psychiatric drug expenditures are measured in Euro per quarter. Standard errors in parentheses are clustered on industry level, , $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

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Results - health related

	(1)	(2)	(3)	(4)	Sample mean
Doctors visits	0.0895	0.1047	0.1041	0.0927	4.7733
	(0.0606)	(0.0574)	(0.0598)	(0.0582)	(7.9735)
Health spa stay	-0.0001	-0.0001	-0.0001	-0.0001	0.0032
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0565)
Psychiatric drug use	0.0007	0.0010	0.0008	0.0009	0.0162
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.1264)
Psychiatric drug expenditures	0.0817	0.0561	0.0370	0.0383	0.6450
	(0.0784)	(0.0617)	(0.0544)	(0.0539)	(7.0670)
Individual level fixed effects	✓	✓	✓	✓	
Individual level controls		✓	✓	✓	
Firm level controls		✓	✓	✓	
Industry level fixed effects		✓	✓	✓	
Linear time trend			✓	✓	
Quarter specific cohort trends				✓	
Observations			8,158,793		

Note: Doctor visits, health spa stays, and sick leaves are measured in days per quarter. Psychiatric drug use is reported as 1 if they were consumed during a quarter and 0 otherwise. Psychiatric drug expenditures are measured in Euro per quarter. Standard errors in parentheses are clustered on industry level. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Conclusion

- Result
  - survivors do not increase sick leaves after ML
  - single day sick leaves do not increase (against shirking)
  - other health outcomes are zero
  - BUT: no information on whether employees go to work despite sickness
- Contributions
  - No absenteeism increase after ML (vs. experiments)
  - we applied a plausible identification strategy for registry data
- Limitations
  - we cannot identify the channel(s) that lead to or prevent sick leaves (net effects might be zero)
  - we still encounter some problems with the data preparation

Prospect and ambitions

- Data
  - renewed bottom-up data preparation
  - introduce new medical outcomes
  - Tune matching
- Analysis
  - Investigate other control groups
  - Explore heterogeneous effects
    - **individual:** blue/white collar, age, sex,...
    - **firm-level:** size of firm, magnitude of ML
    - **industry-level**
  - Expand time horizon of Analysis (short and medium term effects)
  - narrow down indicators of possible channels (delayed sick leaves, increased exit rates, ...)

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