

# Automatic Reaction – What Happens to Workers at Firms that Automate?

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# Longstanding concern: Automation threatens work

1. Luddites—Skilled weavers in the 19th century
2. U.S. Labor Secretary James Davis in 1927
3. Lyndon Johnson 1964 “Blue-Ribbon Presidential Commission on Technology, Automation, and Economic Progress”
4. Wassily Leontief in 1982:  
Role of workers will diminish — like horses
5. At present

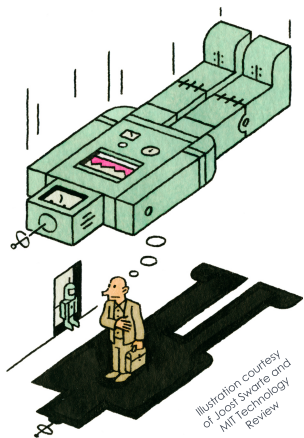


Illustration courtesy  
of Joost Swarte and  
MIT Technology  
Review

# Automation and work

- **Theory: automation** technologies are **labor-replacing** – may lead to labor displacement even in aggregate
  - Autor-Levy-Murnane '03, Acemoglu-Autor '11, Acemoglu-Restrepo '18, Benzell-Kotlikoff-Lagarda-Sachs '18, Martinez '19, Susskind '17
- **Existing empirical evidence** on automation studies the (mostly aggregate) impact of the adoption of **robots** (mostly in manufacturing sectors):
  - Acemoglu-Restrepo '18, Dauth-Findeisen-Suedekum-Woessner '18, Graetz-Michaels '18, Koch-Manuylov-Smolka '19
- Lack empirical evidence on **how automation impacts individual workers**

# Contributions of this paper

- Examine **worker-level impacts** of automation
- Directly measure **firm-level automation** expenditures across **all private non-financial sectors**
- Exploit the timing of **automation events** at the firm level for empirical identification
- **Compare** the worker impacts of **automation and computerization**

# Preview of main findings

- 1 Automation leads to **displacement** for incumbent workers
  - Firm separation  $\uparrow$   $\rightarrow$  Non-employment  $\uparrow$   $\rightarrow$  **Annual earnings**  $\downarrow$
  - **No wage scarring**, but earnings losses only partially offset by benefits
- 2 Affected workers more likely to **switch industries** and enter **early retirement**
- 3 Effects are **pervasive** across industries and worker types
- 4 Automation appears to be **more labor-displacing than computerization**

# Agenda

- 1 Introduction
- 2 Data
- 3 Empirical approach
- 4 Worker-level impacts
- 5 Firm-level changes
- 6 Automation versus computerization
- 7 Conclusions

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- 1 Introduction
- 2 **Data**
  - Data sources
    - Summary statistics for automation costs
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# Data sources from Statistics Netherlands

- Annual **survey of private non-financial firms** (covers all firms with >50 employees and samples smaller firms) which includes a question on **automation costs**
- Administrative daily **matched employer-employee records**
- Years **2000-2016**
- **36K unique firms** with at least 3 yrs of automation cost data employing **4.9M workers** annually on average

▶ Data cleaning



# Automation costs

- Automation costs are an **official bookkeeping entry**
- Defined as costs of **third-party automation services**
  - Includes expenditures on custom software (excl. licensing costs for pre-packaged software)
  - Don't know the specific technology but includes self-service check-out, warehouse and storage systems, automated customer service, data-driven decision making, robot integrators, ...
- Expenditures at the **firm level** and in **all (non-financial private) sectors**

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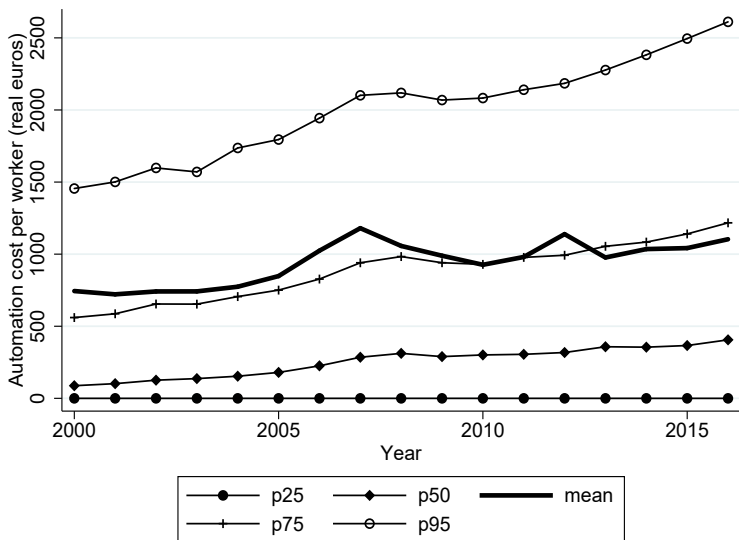
# Firm-level automation cost distributions

	<b>Total cost cost (€)</b>	<b>Cost per worker (€)</b>	<b>Cost share (%)</b>
p5	0	0	0
p10	0	0	0
p25	0	0	0
p50	10,508	257	0.15
p75	48,000	899	0.47
p90	175,083	2,058	1.05
p95	412,945	3,305	1.69
<b>mean</b>	<b>192,390</b>	<b>953</b>	<b>0.44</b>
<b>mean excl. zeros</b>	<b>280,703</b>	<b>1,391</b>	<b>0.64</b>
N firms × years		240,337	
N with 0 costs		31%	

# Mean firm-level automation costs by sector [▶ by firm size](#)

<b>Sector</b>	<b>Cost per worker (€)</b>	<b>Cost share (%)</b>	<i>N Firm x yr</i>
Manufacturing	986	0.36	44,636
Construction	415	0.20	28,774
Wholesale & retail trade	1,075	0.31	75,421
Transportation & storage	834	0.42	21,235
Accommodation & food serving	220	0.29	6,761
Information & communication	1,636	0.85	16,854
Prof'l, scientific, & techn'l act's	1,174	1.02	23,692
Admin & support act's	761	0.49	22,964

# Automation costs per worker over time



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- 1 Introduction
- 2 Data
- 3 Empirical approach
  - Defining automation spikes
    - How do firms with automation spikes differ?
    - An event-study DiD design
- 4 Worker-level impacts
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## Defining automation spikes

- Firm  $j$  has **automation cost share spike** in year  $\tau$  if its real automation costs  $AC_{j\tau}$  relative to real total operating costs (excl. automation costs) averaged across all years are at least thrice the average firm-level cost share (excluding year  $\tau$ ):

$$spike_{j\tau} = \mathbb{1} \left\{ \frac{AC_{j\tau}}{\overline{TC}_{j,t}} \geq 3 \times \frac{\overline{AC}_{j,t \neq \tau}}{\overline{TC}_{j,t}} \right\}$$

where  $\mathbb{1}\{\dots\}$  denotes the indicator function

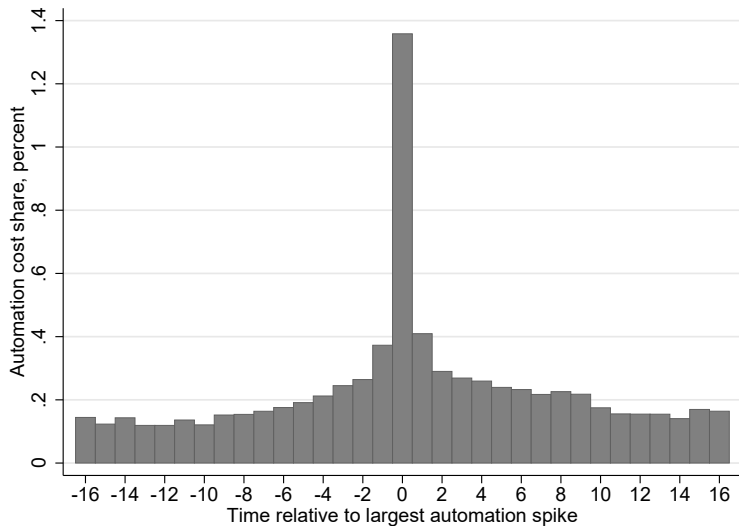
- **Firm-specific measure:** identifies automation events that are large for the firm, independent of firm's initial automation expenditure level

# Automation spike frequencies

<b>Spike frequency over 2000-2016</b>	<b>N firms</b>	<b>% of N firms</b>
0	26,015	71.3
1	8,411	23.0
2	1,764	4.8
3	267	0.7
4	30	0.1
5	4	0.0
Total	36,491	100.0



# Automation cost shares for spikers: spikes are events



# Why do firms experience automation spikes?

- Spikes → **investment is lumpy**: significant share of investment occurs in episodes of disproportionately large quantities
- Spikes arise when investment is **irreversible** and there are **indivisibilities**
  - Under uncertainty, irreversibility creates option value to waiting (Pindyck '91, Nilsen-Schiantarelli '03)
  - Indivisibilities arise from fixed adjustment costs (Cooper-Haltiwanger-Power '99, Doms-Dunne '98, Rothschild '71).
- Major **automation** investments likely include:
  - Substantial **irreversible investments** in custom software and training;
  - **Fixed adjustment costs** from reorganizing production.

# Agenda

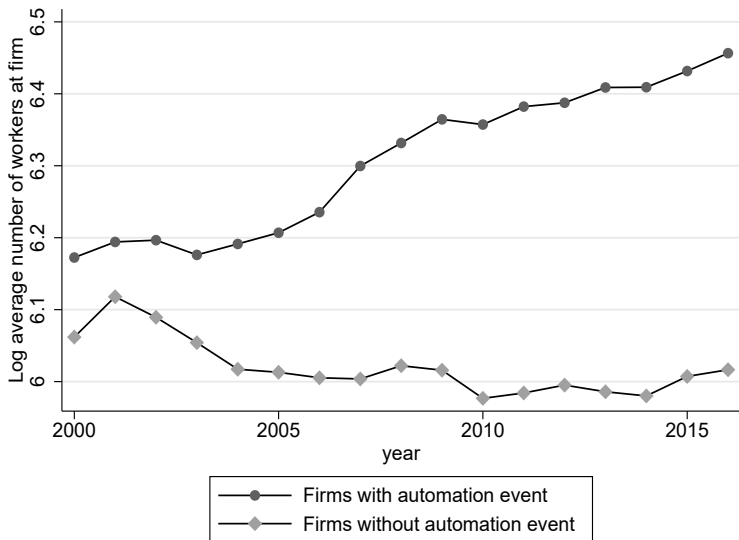
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# How do firms with automation spikes differ?

<b>Firm type</b>	<b>Mean automation cost:</b>		
	level (€)	per worker (€)	share (%)
No automation spike	245,070	1,389	0.62
$\geq 1$ automation spike	359,797	2,547	1.29

for 36K firms with at least 3 yrs of automation cost data

# Log number of employees



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# Leveraging automation cost spikes for identification

- Automation cost spikes are a **big event** for the firm (no “run-of-the-mill” automation), aiding identification
- Assume **timing of automation spikes is random** (conditional on observables) **for incumbent workers**
  - *Related event study approaches*: Borusyak-Jaravel '18;  
Duggan-Garthwaite-Goyal '16; Fadlon-Nielsen '17; He '18; Miller '17;  
Lafortune-Rothstein-Schanzenbach '18;  
Dobkin-Finkelstein-Kluender-Notowidigdo '18
  - Uncertainty & indivisibility → small  $\Delta$  in payoff to automating can generate substantial  $\Delta$  in the timing of investment (Bessen '99)

# Defining treatment and controls

- Incumbent workers at a firm are **treated** in year  $\tau$  if that firm undergoes an automation spike in year  $\tau$
- Incumbent workers employed at firms that spike at  $\tau + k$  or later are used as **controls** for the years  $\tau - k - 1$ , where we choose  $k = 5$
- Define **incumbent workers**:  $\geq 3$  yrs of firm tenure prior to the automation event (cf. mass lay-off literature)
- **Matching** controls and treated on pre-treatment income, sector, and calendar year (using CEM, see Blackwell-lacus-King-Porro '09, lacus-King-Porro '12) [▶ Matching details](#)



# Empirical model

Estimating equation:

$$y_{ijt} = \alpha + \beta F_i + \sum_{t \neq -1; t = -3}^4 \gamma_t \times l_t + \sum_{t \neq -1; t = -3}^4 \delta_t \times l_t \times treat_i + \lambda X_{ijt} + \varepsilon_{ijt},$$

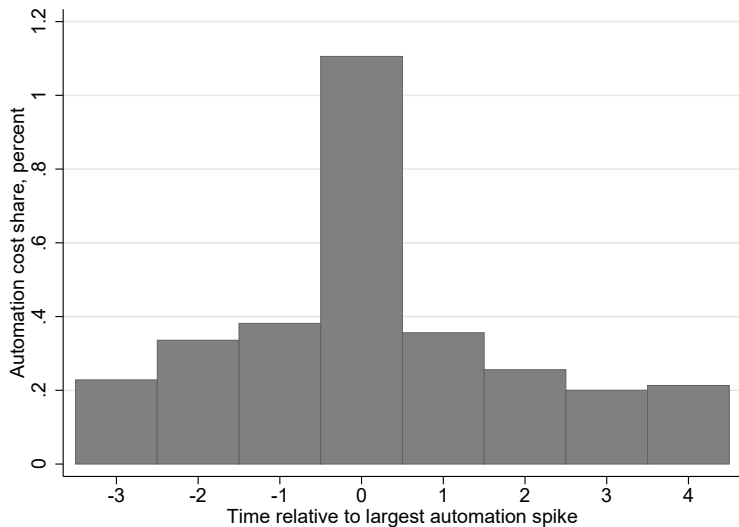
- $i$  indexes workers,  $j$  firms, and  $t$  time measured relative to automation event in year  $\tau$ , i.e.  $t \equiv year - \tau$
- $F_i$  is a **worker fixed-effect**
- $l_t$  is a **time fixed-effect** relative to the event year, with  $t \in \{-3, 4\}$ , and  $t = -1$  as reference category
- $treat_i$  is **treatment indicator** = 1 if worker  $i$  is employed at a firm experiencing an automation event at  $t = 0$

# Empirical model

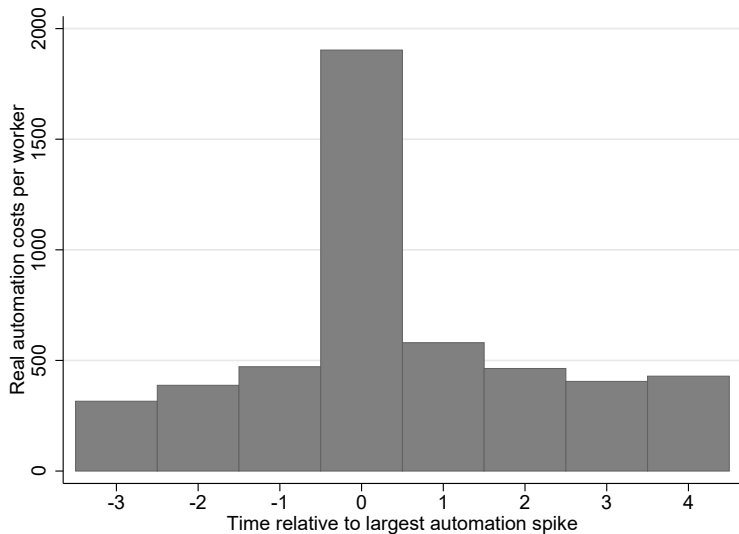
$$y_{ijt} = \alpha + \beta F_i + \sum_{t \neq -1; t = -3}^4 \gamma_t \times l_t + \sum_{t \neq -1; t = -3}^4 \delta_t \times l_t \times treat_i + \lambda X_{ijt} + \varepsilon_{ijt},$$

- **Parameters of interest** are  $\delta_t$ : period  $t$  treatment effect relative to pre-treatment period  $t = -1$
- $X_{ijt}$  are time-varying **controls**: worker age, age<sup>2</sup>, year fixed effects
- **Standard errors** clustered at the treatment level (i.e. event windows for all workers employed at the same firm in  $t - 1$  are one cluster)

# Automation events for treated firms



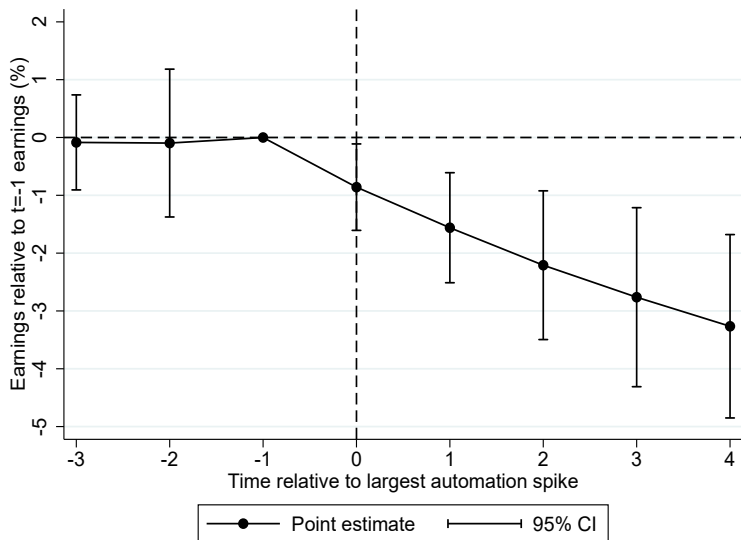
# Automation events for treated firms



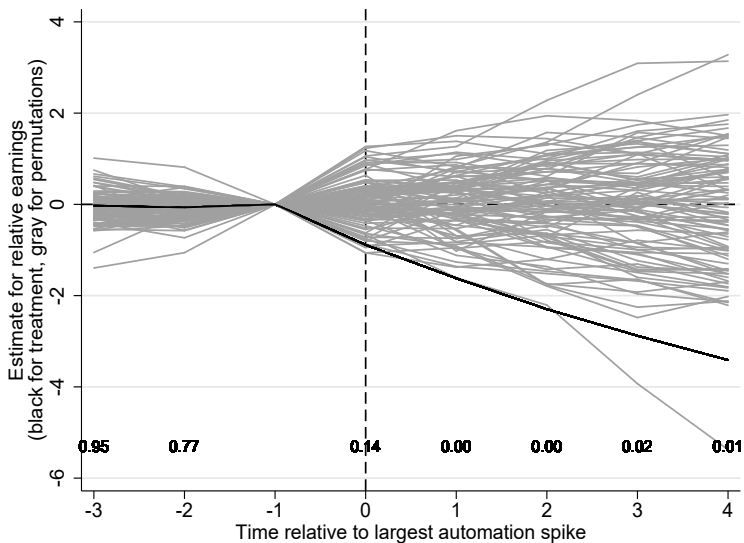
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  - Annual wage income
  - Firm separation, non-employment, and wage rates
  - Other adjustment margins and effect heterogeneity
- 5 Firm-level changes
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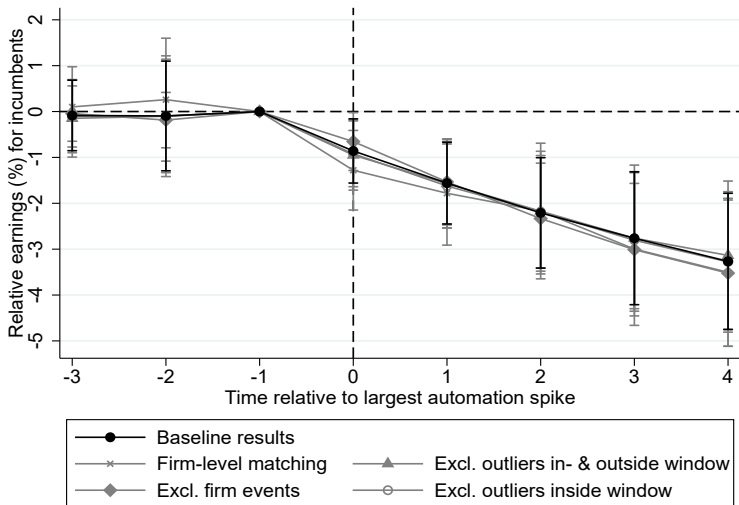
# Annual wage income, percentages



# Annual wage income (%): Randomization test



# Robustness to other events: Annual wage income (%)



Robustness to changes in [▶ spike definition](#) and [▶ model specification](#)

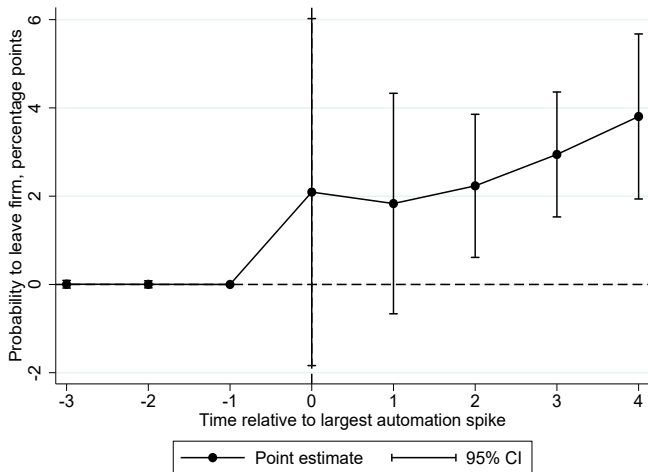


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# Firm separation, hazard rates

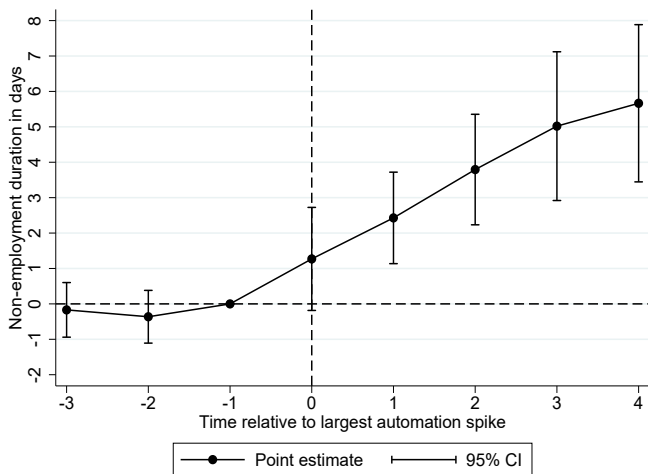
▶ robustness



Hazard rates for CG incumbents are 9.6% in t=0 and 8.8% in t=4 (40%↑)

# Annual days in non-employment

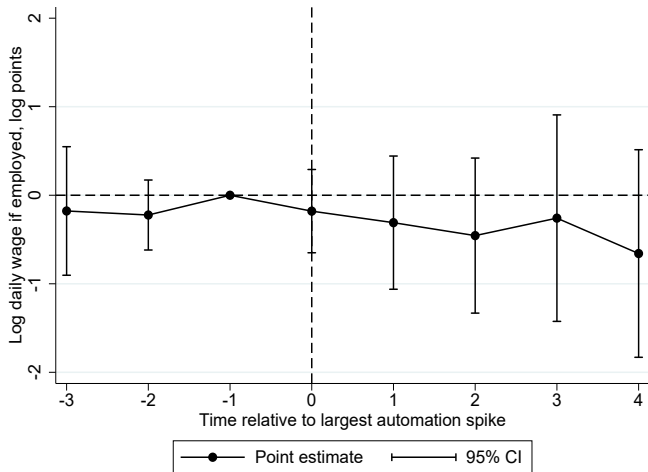
▶ robustness



Annual non-employment days for CG incumbents are 5.7 in  $t=0$  and 28 in  $t=4$  (20%↑)

# Log daily wage

▶ robustness

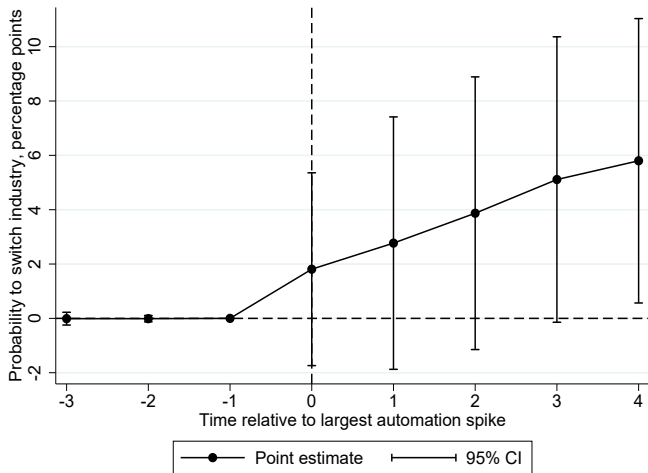


Wage change in log points for CG incumbents is 1.8 in t=0 and 5.4 in t=4

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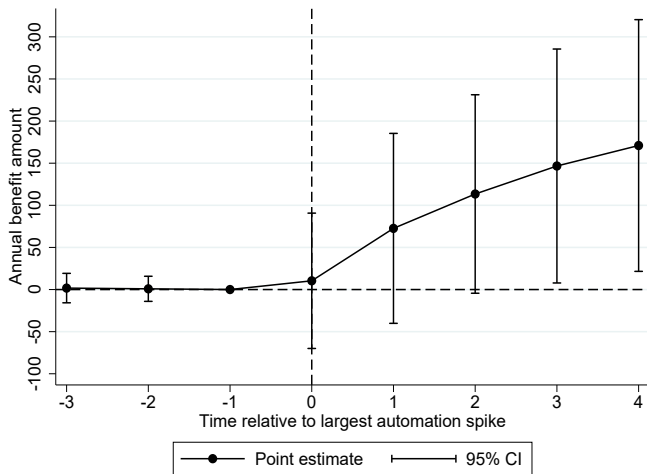
# Probability of switching industries



Industry switch probability for CG incumbents is 7% in t=0 and 30% in t=4 (20%↑)

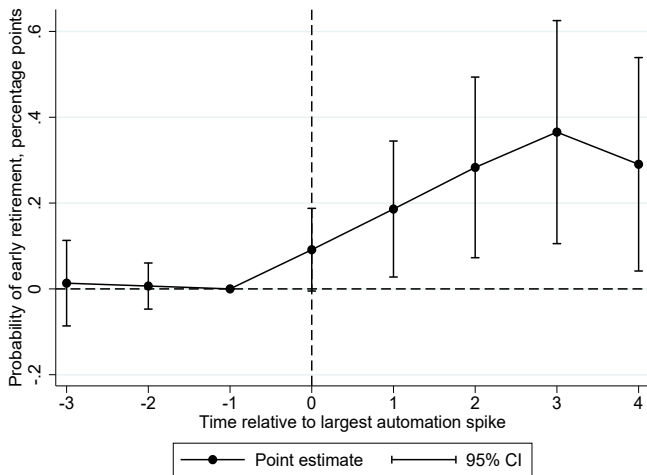
# Annual total benefit income, levels

▶ split by benefit source



Annual benefit income for CG incumbents is EUR 186 in t=0 and EUR 781 in t=4

# Probability of early retirement



Early retirem. probability for CG incumbents is 0.2% in t=0 and 1.5% in t=4 (18%↑)



# Effect heterogeneity

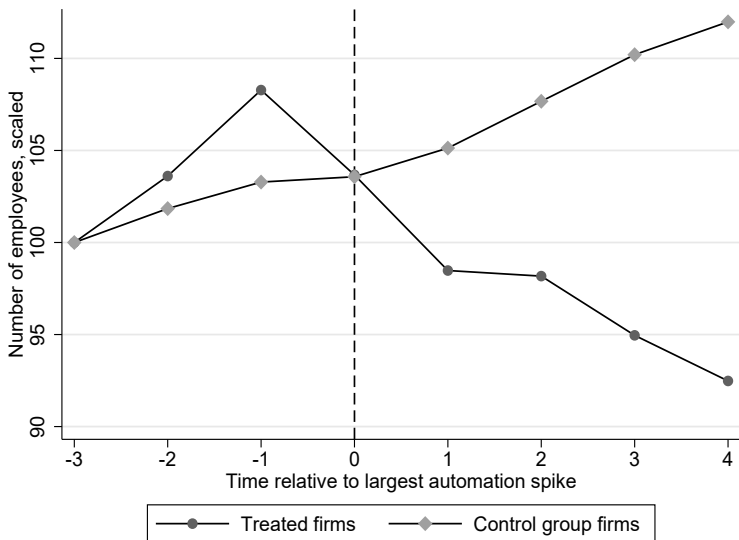
- Displacement effects for incumbent workers pervasive across: ▶ estimates
  - sectors (exception: Accommodation & food serving)
  - firm sizes
  - worker age & gender
  - workers' age-specific wage ranks (“skill level”)
- No displacement effects for the firm's more recent pre-event hires

▶ estimates

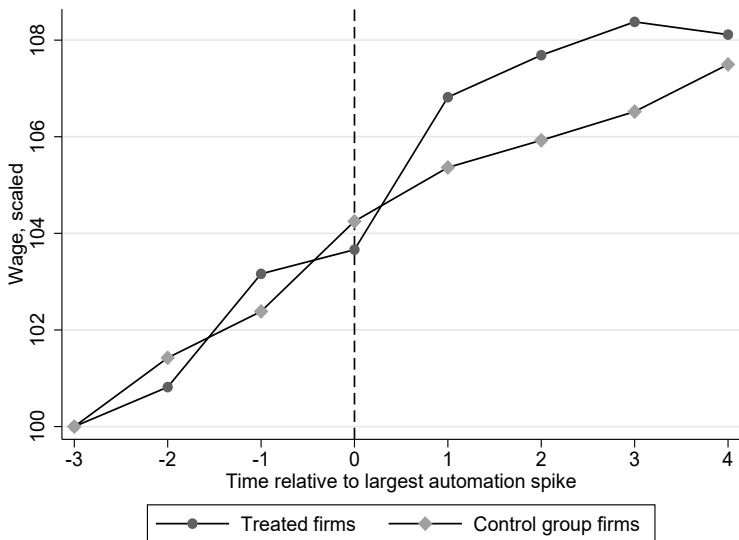
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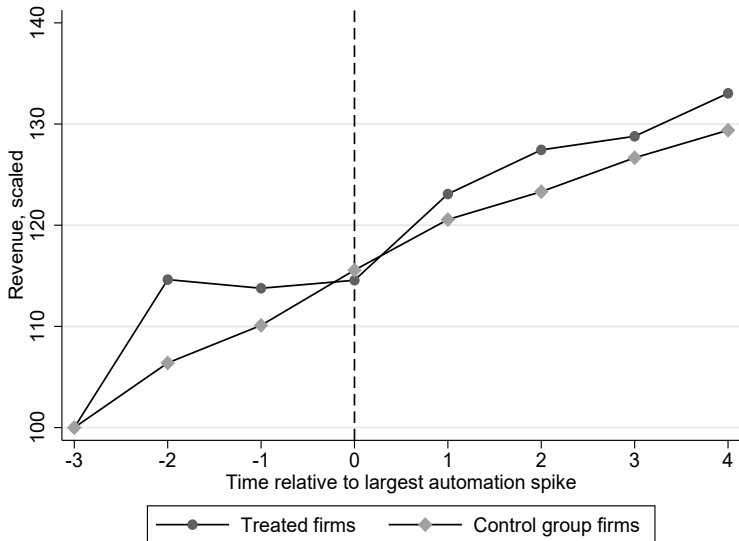
# Employment for treated and control group firms



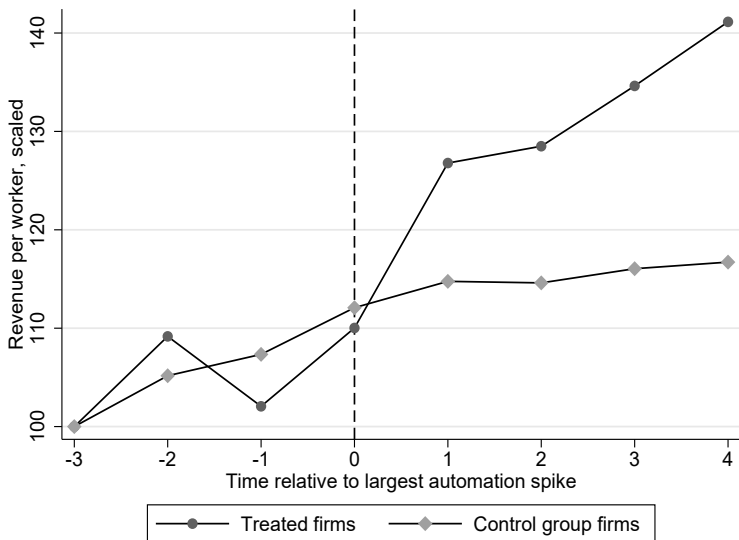
# Mean daily wage for treated and control group firms



# Total revenue for treated and control group firms



## Revenue per worker for treated and control group firms



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# Comparison to computerization

- Are **displacement effects specific to automation?**
- **Compare** worker-level impacts **to other technology**
- Use partially overlapping firm survey on **computer investments**
  - “All data-processing electronic equipment insofar as they can be freely programmed by the user, including all supporting appliances.”
- Use **same event study DiD** design to study **computerization**



# Summary statistics on overlapping sample

	Automation cost (€)		Computer investment (€)	
	<i>level</i>	<i>per worker</i>	<i>level</i>	<i>per worker</i>
p5	0	0	0	0
p10	0	0	0	0
p25	0	0	0	0
p50	16,747	297	5,554	99
p75	69,617	957	31,042	447
p90	241,274	2,175	112,889	1,126
p95	568,915	3,518	250,652	1,868
<b>mean</b>	<b>249,275</b>	<b>1,032</b>	<b>99,666</b>	<b>559</b>
<b>mean excl. zeros</b>	<b>346,396</b>	<b>1,434</b>	<b>155,619</b>	<b>873</b>
N firms × yrs	171,549			

## Automation costs &amp; computer investments by sector

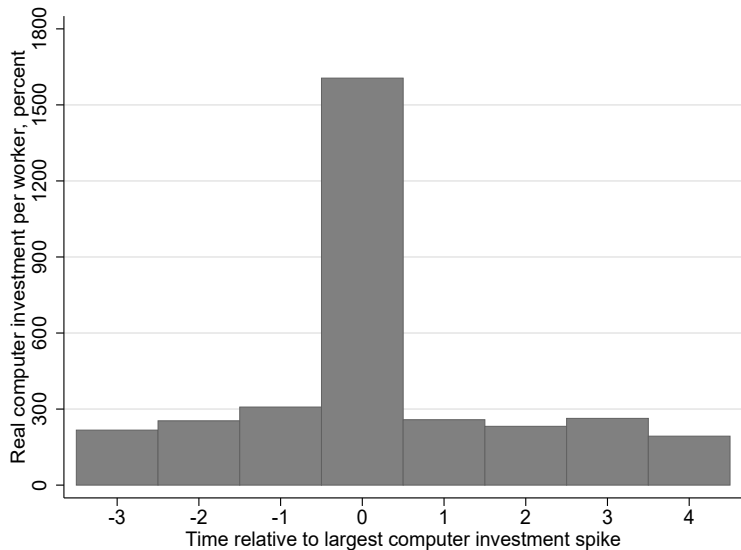
▶ over time

<b>Sector</b>	<b>Autom. cost per worker (€)</b>	<b>Comp. inv. per worker (€)</b>	<b>Autom. to comp.</b>	<i>N Firms × yrs</i>
Manufacturing	998	369	2.7	40,773
Construction	497	215	2.3	18,319
Wholesale & retail trade	1,152	544	2.1	50,381
Transportation & storage	917	456	2.0	15,834
Accommodation & food serving	256	151	1.7	4,462
Information & communication	2,030	2,420	0.8	9,756
Prof'l, scientific, & techn'l act's	1,272	772	1.6	14,708
Admin & support act's	863	388	2.2	17,316

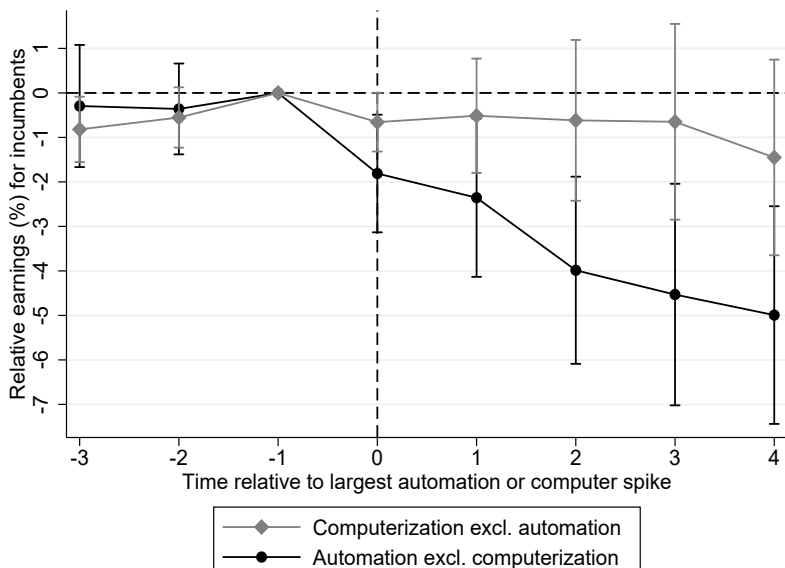
# Spike frequencies, overlapping sample

<b>Nr of events</b>	<b>Percentage of firms with event type:</b>	
	Automation	Computerization
0	71.8	47.9
1	22.5	41.9
2	4.8	9.1
3	0.7	1.1
4	0.1	0.1

# Computer investment event spikes, estimation sample



# Automation versus computerization



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# Conclusions

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  - Firm separation  $\uparrow \rightarrow$  Non-employment  $\uparrow \rightarrow$  **Annual earnings**  $\downarrow$
  - **No wage scarring**, but earnings losses only partially offset by benefits
- 2 Affected workers more likely to **switch industries** and enter **early retirement**
- 3 Effects are **pervasive** across industries and worker types
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# Appendices



## Appendix: Data cleaning

# Data cleaning

We remove the following observations:

- Workers enrolled in full-time studies earning either less than EUR 5K annually or EUR 10 daily on average across the year
- Workers with earnings above EUR 500K annually or EUR 2K daily on average across the year
- Later, we further exclude workers at firms that have:
  - Not a single spike in automation cost shares
  - No event window (7 yrs of consecutive data)
  - Other events in the event window (mergers, takeovers, splits, restructuring)
  - Large (>90%) annual employment changes in the event window or also outside the event window

# Estimation sample

- 36K unique firms have at least 3 yrs of automation cost data
- *Of those*, there are 10K unique firms that have at least one automation spike
- *Of those*, **the estimation sample** are 6K unique firms that have at least 7 yrs of consecutive data, i.e. have an event window
- Those 6K firms employ 1M unique incumbent workers annually on average, resulting in 8.4M worker-year observations in our estimations
- The estimation sample consists of 2K **treated firms** that have observations 3 yrs before and 4 yrs after their spike (that spike between 2003-2011) [◀ Go Back](#)

## Appendix: Matching details

# CEM statistics

- Coarsened Exact Matching (CEM):
  - 1 In each of the three pre-treatment years, separate strata for each 5 percentiles of annual wage + separate bins for the 99th and 99.5th percentiles
  - 2 One year prior to treatment, matched workers must be observed in the same calendar year and work in the same sector
- 30,247 strata
- 98% of treated incumbents are matched; and 93% of control group incumbents are assigned a non-zero weight

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## Appendix: Further summary statistics

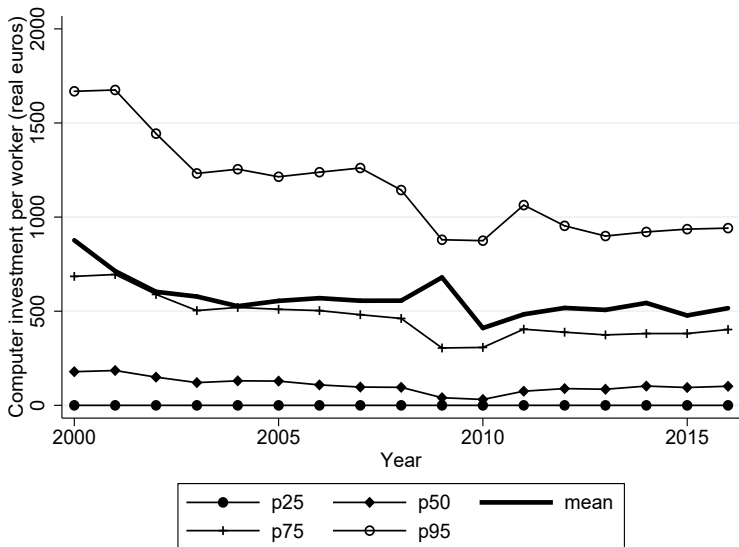
# Automation costs by firm size

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Firm size class	Cost per worker (€)		Cost share (%)		Nr of obs <i>Firm × yr</i>
	Mean	SD	Mean	SD	
1-19 employees	1,114	18,317	0.40	1.27	51,128
20-49 employees	803	4,426	0.42	1.23	86,036
50-99 employees	817	3,142	0.42	1.23	45,797
100-199 employees	930	2,452	0.44	0.92	29,073
200-499 employees	1,186	3,905	0.52	1.17	17,694
≥500 employees	1,656	6,884	0.74	1.53	10,609

# Computer investment per worker over time

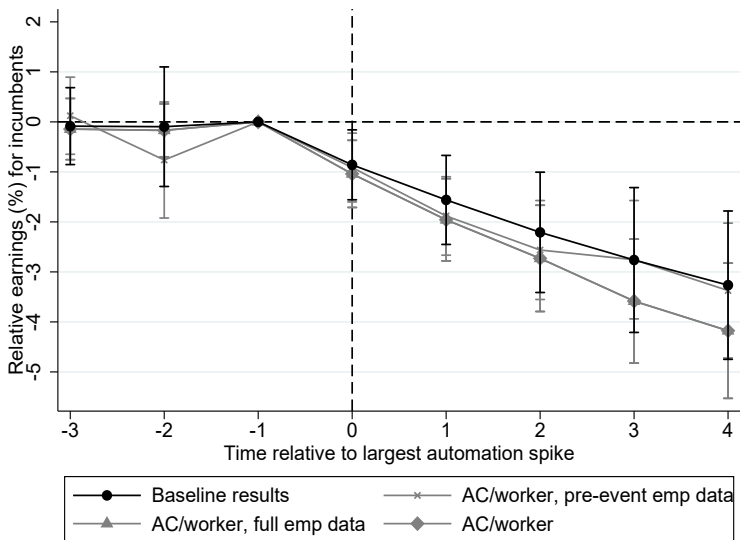
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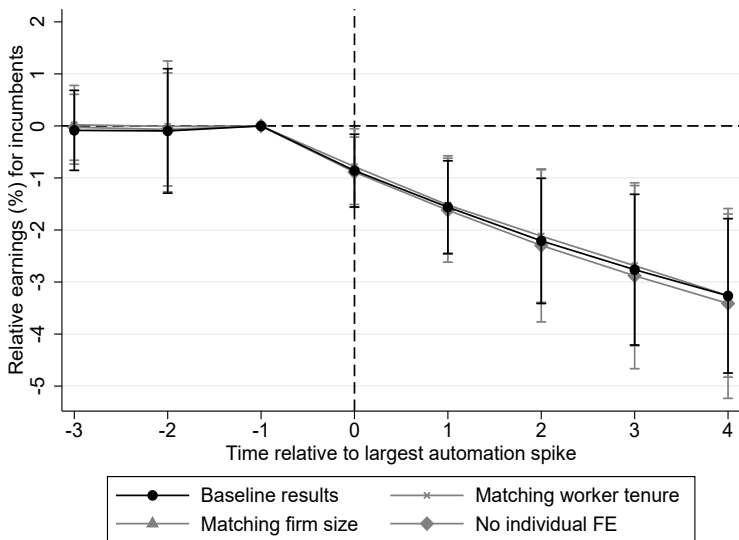
## Appendix: Further robustness checks

# Robustness to spike definition: Annual wage (%) [Go Back](#)



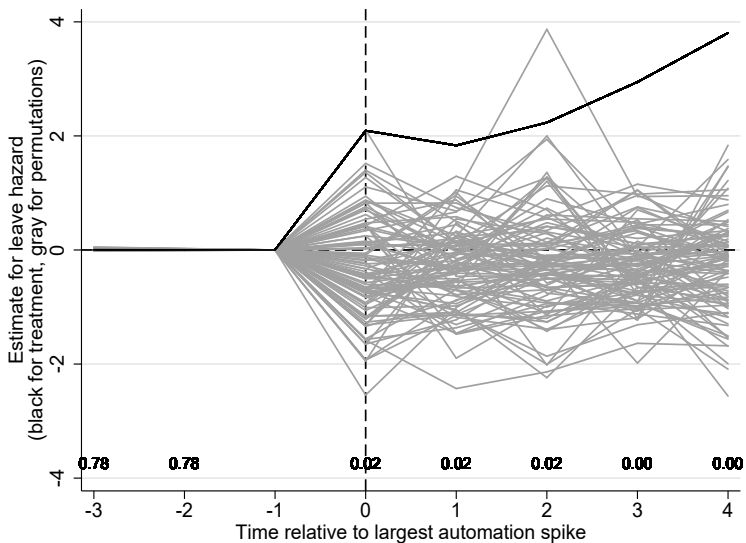
# Robustness to model spec.: Annual wage (%)

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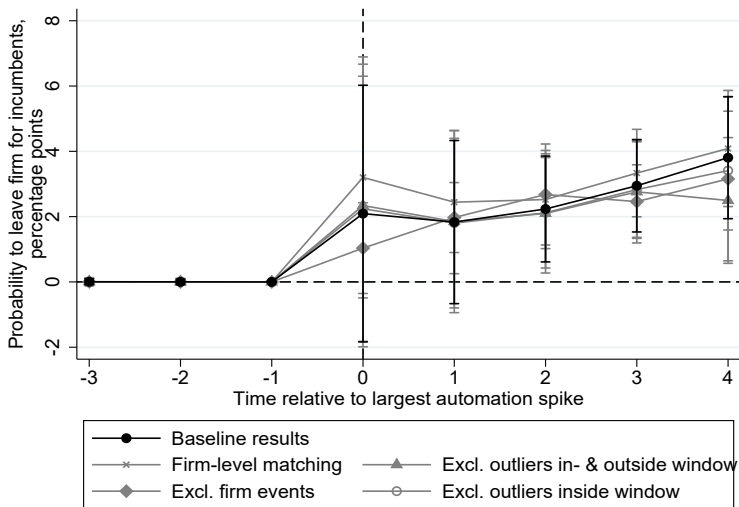
# Randomization test: Firm separation

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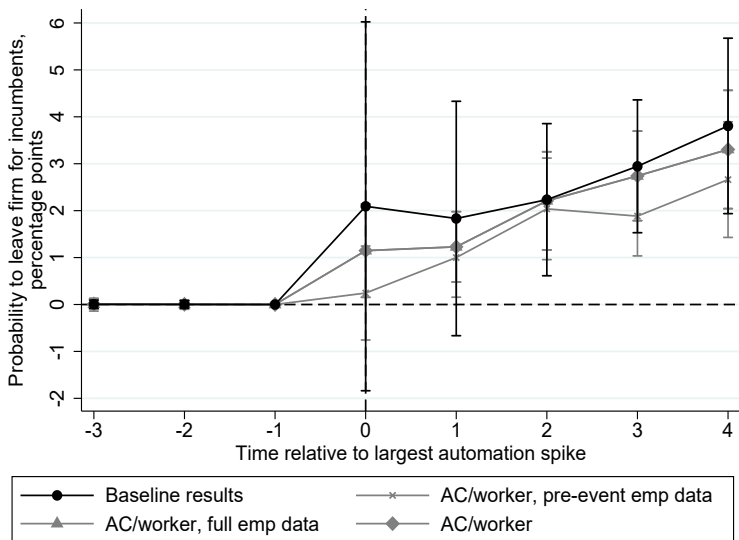
# Robustness to other events: Firm separation

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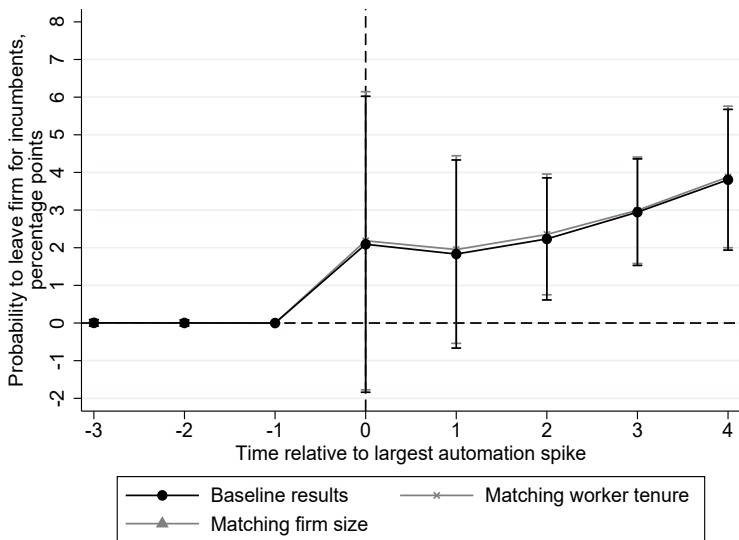
# Robustness to spike definition: Firm separation

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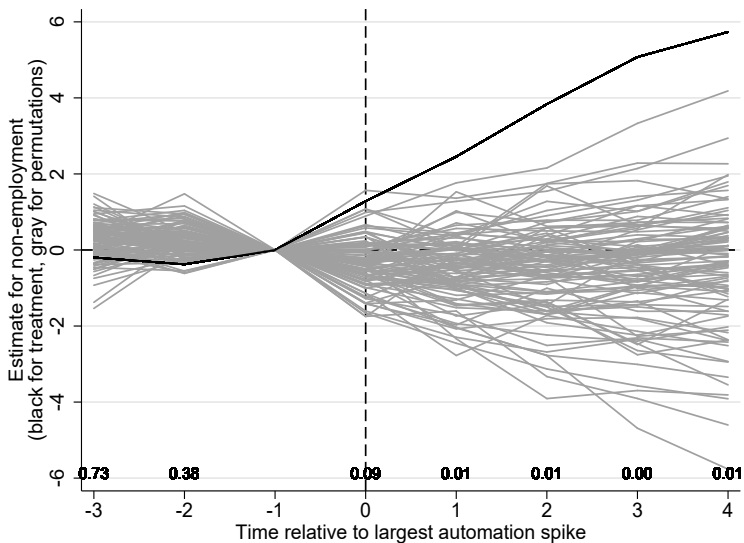
# Robustness to model spec.: Firm separation

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# Non-employment estimates, randomization test

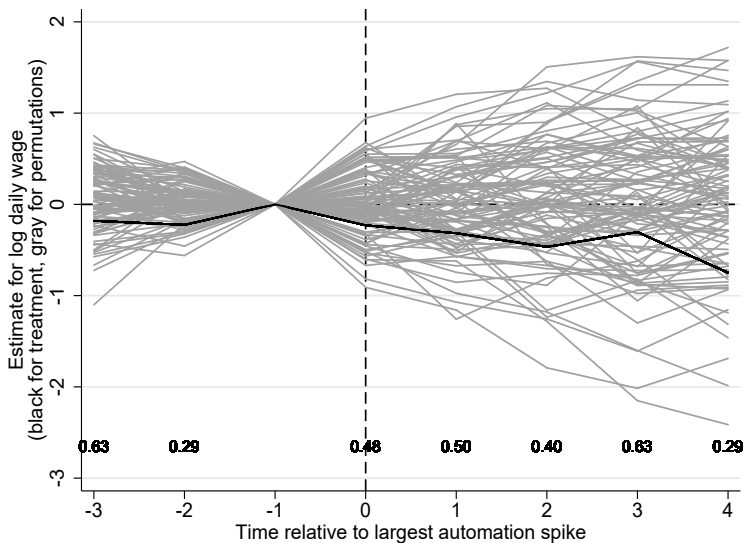
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# Daily wage estimates, randomization test

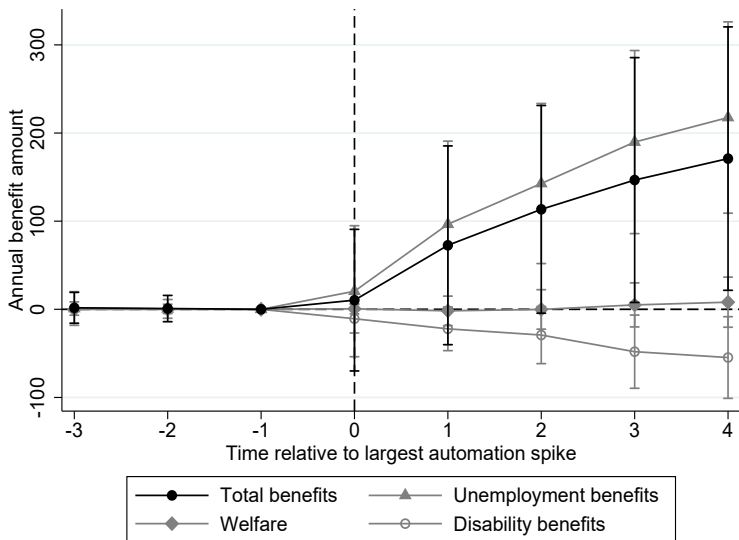
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## Appendix: Further estimates

# Annual benefit income split

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# Heterogeneity in average annual wage impact

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(1) Age		(3) Gender	
Age <30 (ref)	-1.84 (3.19)	Male (ref)	-1.52*** (0.57)
<i>Deviations from reference group for:</i>		<i>Deviations from reference group for:</i>	
Age 30-39	-0.24 (3.73)	Female	-1.39 (0.97)
Age 40-49	0.42 (3.60)	(4) Sector	
Age 50+	-1.20 (3.94)	Manufacturing (ref)	-1.98** (0.99)
(2) Firm size		<i>Deviations from reference group for:</i>	
500+ employees (ref)	-1.53 (1.35)	Construction	1.05 (1.73)
<i>Deviations from reference group for:</i>		Wholesale & retail trade	-2.23 (1.51)
200-499 employees	1.21 (1.77)	Transportation & storage	0.71 (1.79)
100-199 employees	-2.19 (1.77)	Accommodation & food serving	4.57** (2.32)
50-99 employees	0.17 (1.57)	Information and communication	-0.25 (1.76)
20-49 employees	-2.18 (1.46)	Prof'l, scientific, & techn'l act's	-0.24 (1.80)
1-19 employees	-2.06 (1.52)	Administrative & support act's	1.55 (2.01)

# Heterogeneity in average annual wage impact

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(1) Overall age-specific wage quartile		(2) Within-firm age-specific wage quartile	
Bottom quartile (ref)	-2.26* (1.20)	Bottom quartile (ref)	-1.06 (1.26)
<i>Deviations from reference group for:</i>		<i>Deviations from reference group for:</i>	
Second quartile	0.17 (1.10)	Second quartile	-1.37 (1.12)
Third quartile	0.48 (1.39)	Third quartile	-0.75 (1.31)
Top quartile	0.09 (1.65)	Top quartile	-1.62 (1.56)

# Annual earnings for incumbents vs. recent hires

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