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

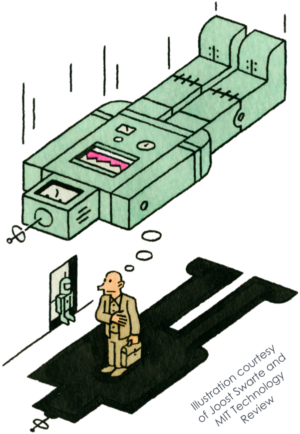


Illustration courtesy of Joost Swarte and MIT Technology Review

Automation and work

- **Theory**: **automation** technologies are **labor-replacing**
  - Autor-Levy-Murnane '03, Acemoglu-Autor '11, Acemoglu-Restrepo '18, '19, 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
- **Direct empirical evidence on worker-level impacts of automation is lacking**

Contributions of this paper

1. Examine **worker-level impacts** of automation
2. Directly measure **firm-level automation** expenditures across **all private non-financial sectors**
3. Exploit the timing of **automation events** at the firm level for empirical identification
4. **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

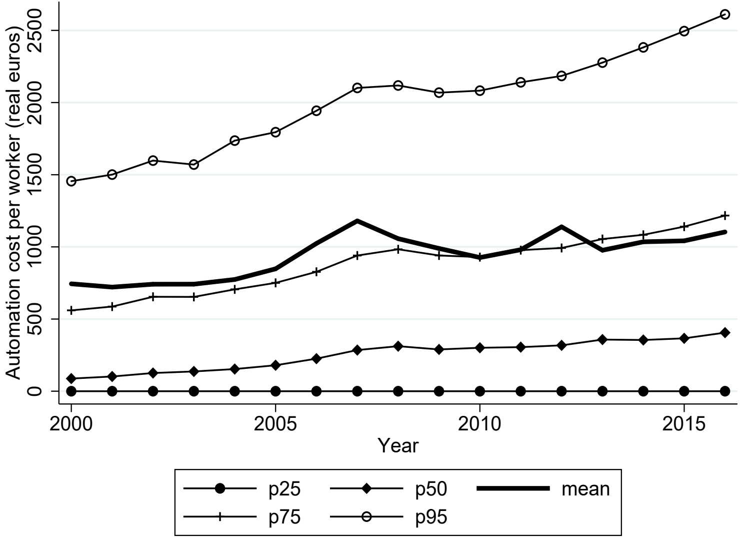
1. Data
   - Data sources
   - Summary statistics for automation costs
2. Empirical approach
3. Worker-level impacts
4. Automation versus computerization
5. Conclusions

Data from Statistics Netherlands

▸ Data cleaning

- Annual **survey of private non-financial firms**, includes question on **automation costs**
  - "Cost of third-party automation services"
  - Official book-keeping entry
  - Don't know the specific technology but e.g. self-service check-out, warehouse and storage systems, automated customer service, data-driven decision making, robot integrators, ...
- Administrative daily **matched employer-employee records**
- Years **2000-2016**

Automation costs per worker over time



Agenda

1. Data
2. Empirical approach
   - Defining automation spikes
   - Empirical design
3. Worker-level impacts
4. Automation versus computerization
5. Conclusions

Defining automation spikes

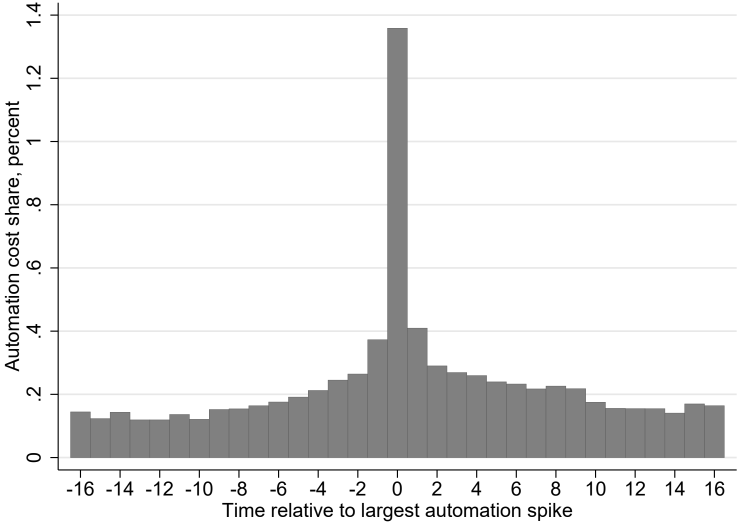
- Firm j has **automation cost share spike** in year τ if its real automation costs $AC_{j\tau}$ relative to real total operating costs (excl. automation costs) averaged across all years are at least thrice the average firm-level cost share (excluding year τ):

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

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

- **Firm-specific measure**: identifies automation events that are large for the firm

Automation cost shares for spikers: spikes are events



Why do firms experience automation spikes?

- Spikes $\rightarrow$ **investment is lumpy**
- Spikes arise when investment is **irreversible** and there are **indivisibilities** from fixed adjustment costs
  - Cooper-Haltiwanger-Power '99, Doms-Dunne '98, Nilsen-Schiantarelli '03, Pindyck '91, Rothschild '71
- Major **automation** investments likely include:
  - **Irreversible investments** in custom software and training;
  - **Fixed adjustment costs** from reorganizing production.

How do firms with automation spikes differ?

Firm type	N firms	Mean annual automation cost: total	per worker	Mean annual empl. growth
No spike	26,015	€245,070	€1,389	0.0%
$\geq$1 spike	10,497	€359,797	€2,547	1.8%

Defining treatment and controls

- Workers at a firm are **treated** in year τ if that firm undergoes an automation spike in year τ
- Workers employed at firms that spike at $\tau + k$ or later are used as **controls** for the years $\tau - k - 1$, where we choose $k = 5$
- Restrict sample to **incumbent workers**: ≥ 3 yrs of firm tenure prior to automation event
- **Matching** controls and treated on pre-treatment income, sector, and calendar year ▸ Matching details

$\rightarrow$ **Identifying assumption:** timing of automation spikes is random from perspective of incumbent workers.

Estimating equation

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

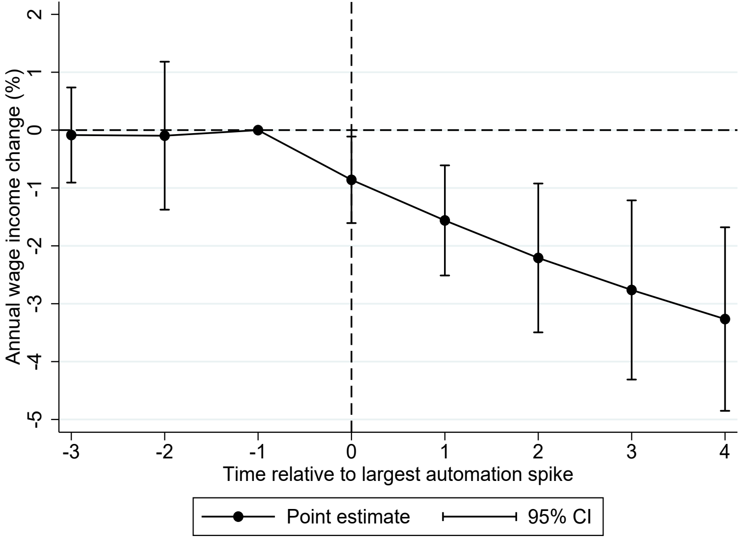
- i workers; j firms; t time measured relative to automation event in year τ, i.e. $t \equiv year - \tau$
- F_i worker fixed-effect; I_t time fixed-effect; X_{ijt} time-varying controls
- $treat_i$ treatment indicator = 1 if worker i is employed at a firm experiencing an automation event at $t = 0$
- δ_t are period t treatment effects relative to pre-treatment period $t = -1$

- Se's clustered at the treatment level

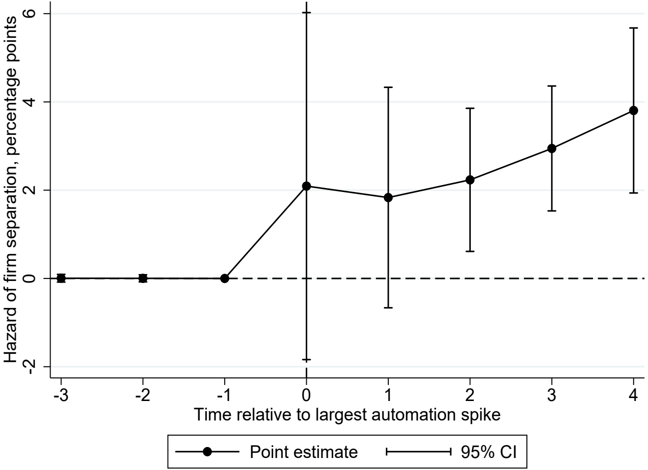
Agenda

1. Data
2. Empirical approach
3. Worker-level impacts
   - Annual wage income for incumbent workers
   - Firm separation, non-employment, and wage rates
   - Other adjustment margins and effect heterogeneity
4. Automation versus computerization
5. Conclusions

Annual wage income, percentages

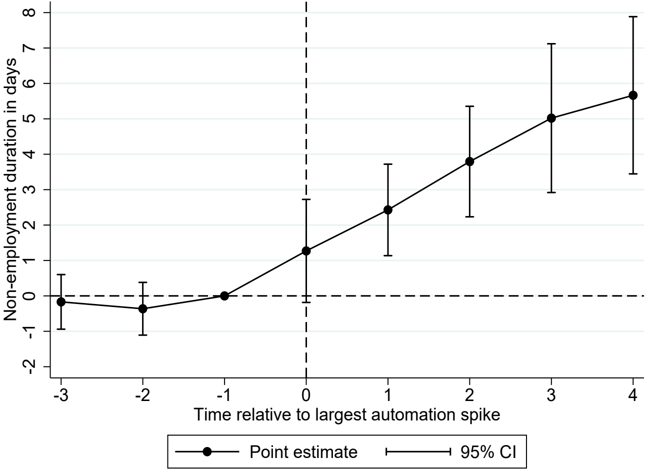


Firm separation, hazard rates



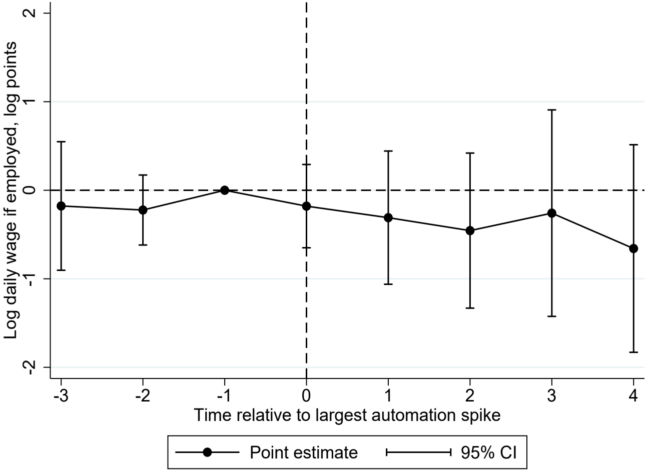
Hazard rates for CG incumbents are 9.6% in t=0 and 8.8% in t=4 (40%↑)

Annual days in non-employment



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

Log daily wage



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

Robustness checks

1. Results are similar when **eliminating other firm-level events** estimates
   - Removing firms with administrative changes (M & A's, take-overs, restructuring, ..)
   - Removing firms with (suspected) management change
   - Matching on firm-level pre-trend in employment
   - Excluding outliers in firm-level employment growth
2. Results survive a **permutation test** estimates
3. Results are similar for **different model specifications** estimates
4. Results are similar for **different spike definitions** estimates

Probability of switching industries

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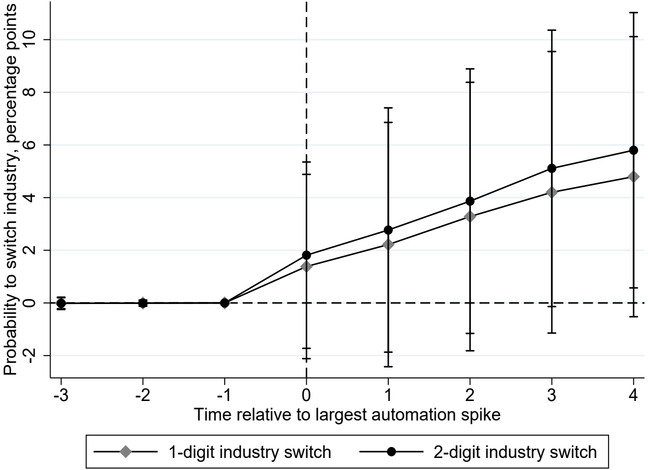

Industry switch probability for CG incumbents is 7% in t=0 and 30% in t=4 (20%↑)

Probability of early retirement

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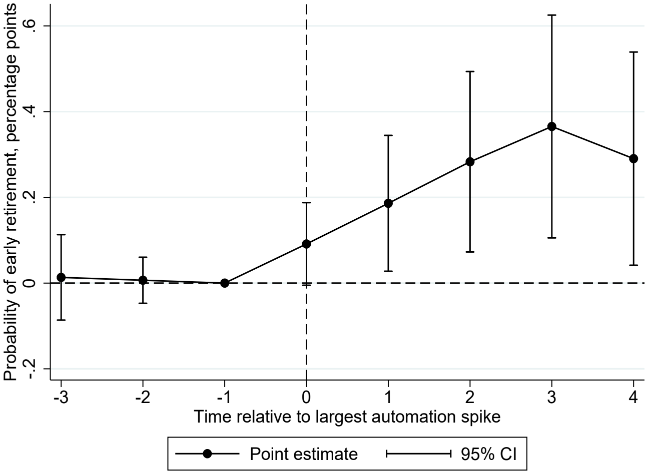


Early retirem. probability for CG incumbents is 0.2% in t=0 and 1.5% in t=4 (18%↑)

Summary of other results

1. 13% of wage income losses are compensated by **social security benefits** ▸ estimates
2. Displacement effects for incumbent workers **pervasive** across: ▸ estimates
    - sectors
    - firm sizes
    - worker age & gender
    - workers' age-specific wage ranks
3. No displacement effects for the firm's more recent **pre-event hires** ▸ estimates

Agenda

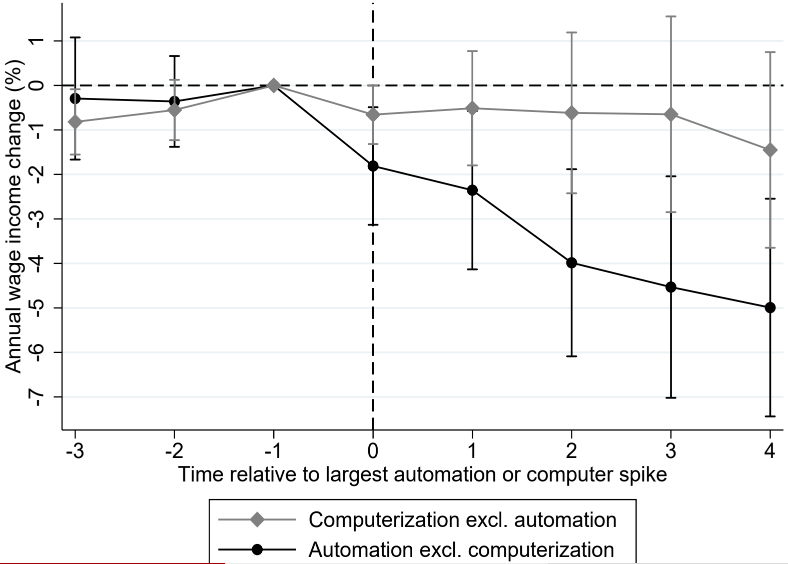
Comparison to computerization

- Are **displacement effects specific to automation?**
- **Compare** worker-level impacts of **automation to computerization**
- 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 empirical design

Spike frequencies, overlapping sample

	Percentage of firms with event type:	
Nr of events	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

Automation versus computerization



Agenda

Conclusions

1. Automation leads to **displacement** for incumbent workers
   - Firm separation $\uparrow$ $\rightarrow$ Non-employment $\uparrow$ $\rightarrow$ **Annual earnings** $\downarrow$
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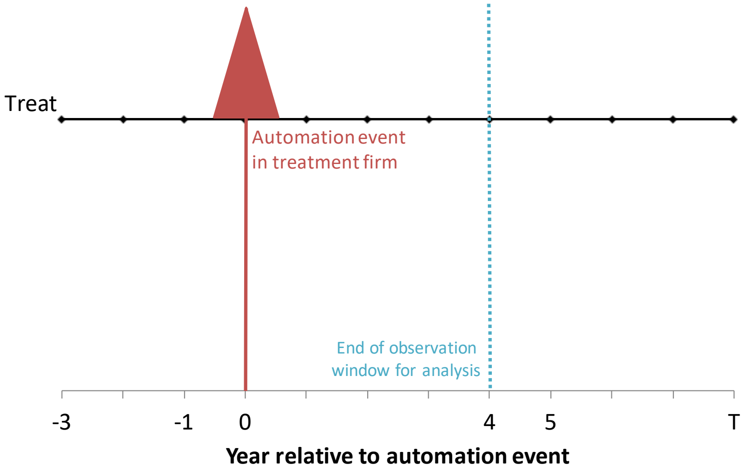
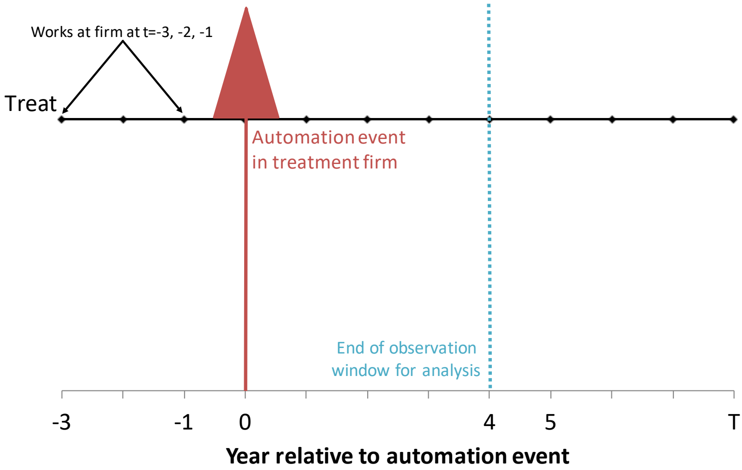
Appendices

Appendix: Defining treatment and controls

Defining treatment and controls



Defining treatment and controls



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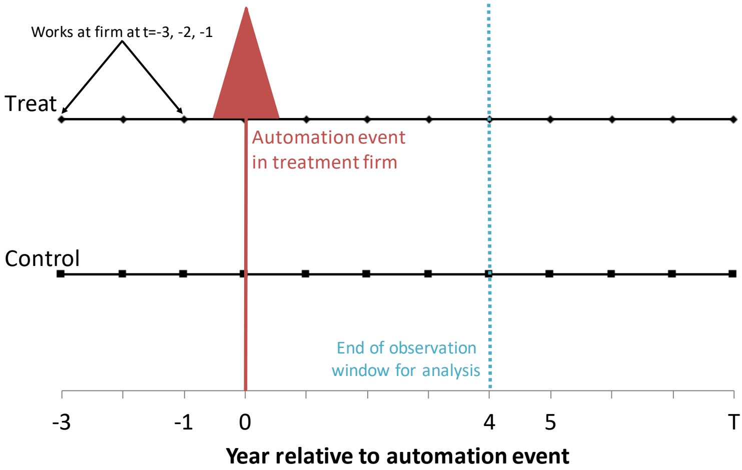

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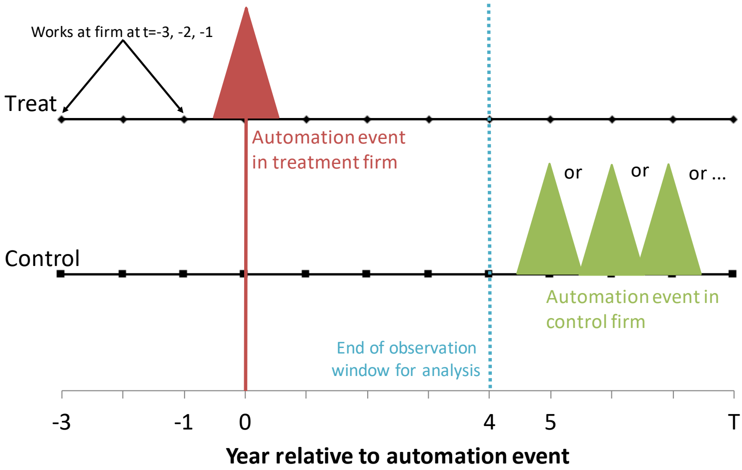
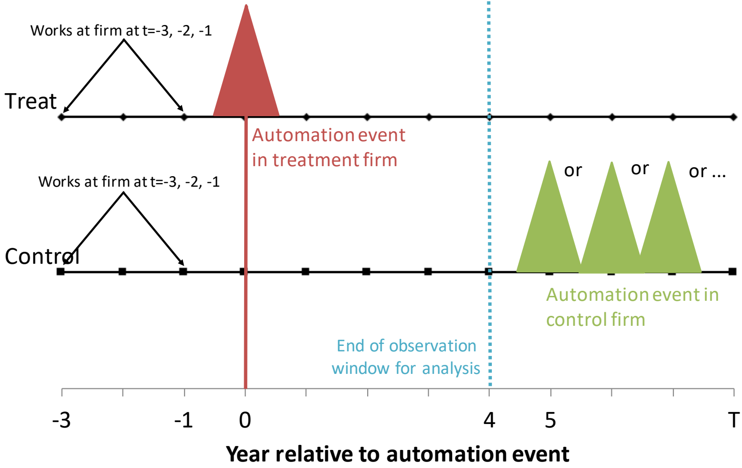


Defining treatment and controls ▸ sample construction



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

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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 (€) Mean	Cost per worker (€) SD	Cost share (%) Mean	Cost share (%) SD	Nr of obs *Firm × yr*
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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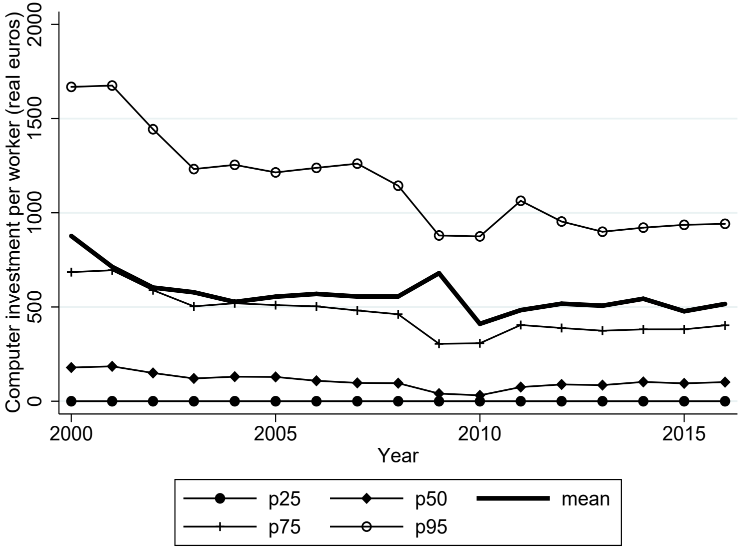

Appendix: Further robustness checks

Annual wage income (%): Randomization test

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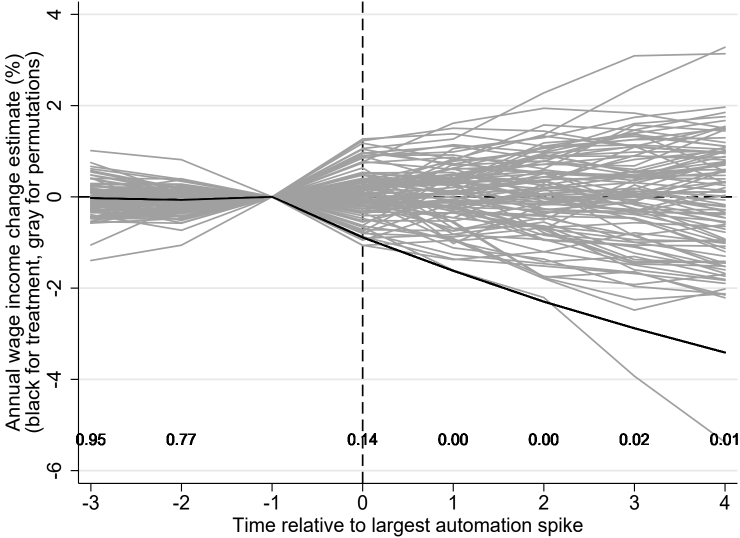

Robustness to other events: Annual wage income (%)

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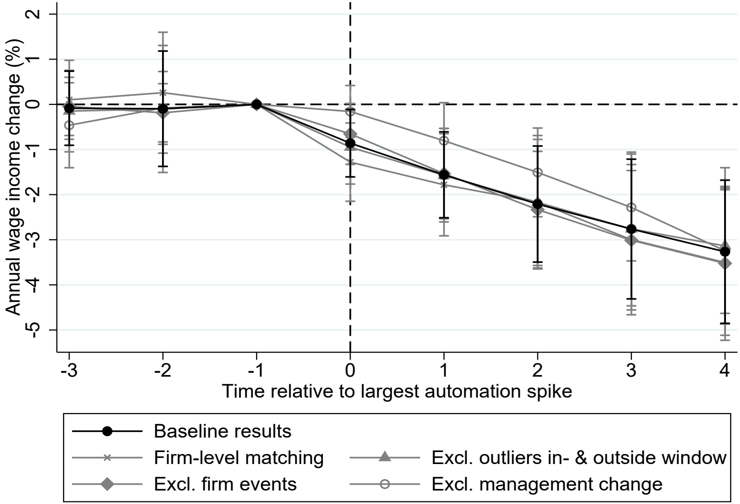

Robustness to spike definition: Annual wage (%)

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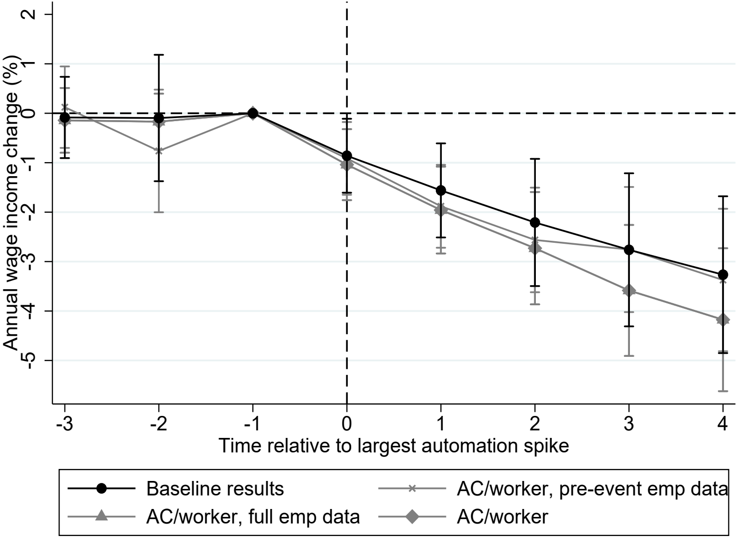

Robustness to model spec.: Annual wage (%)

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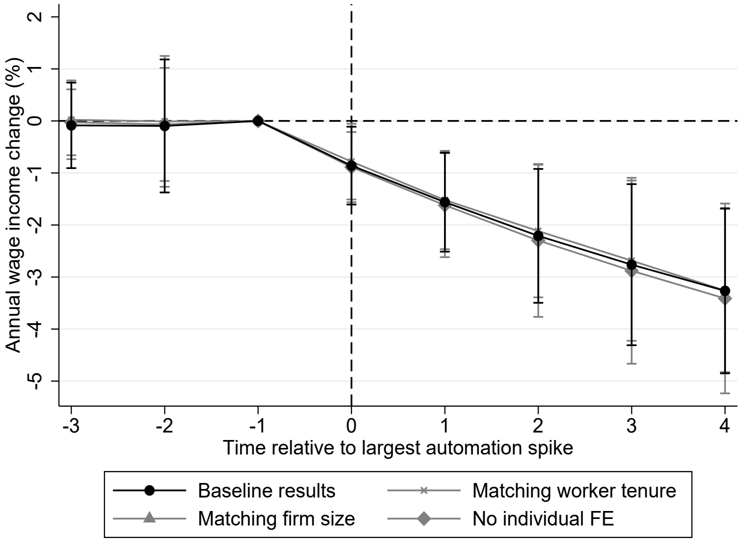

Randomization test: Firm separation

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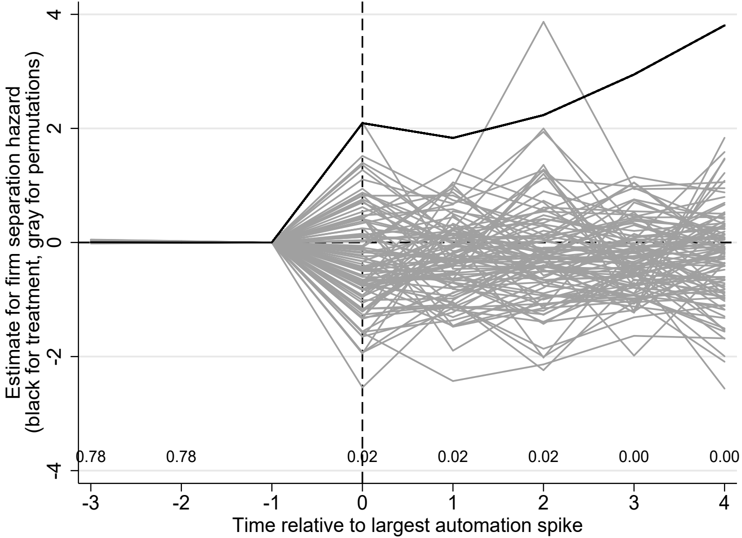

Robustness to other events: Firm separation

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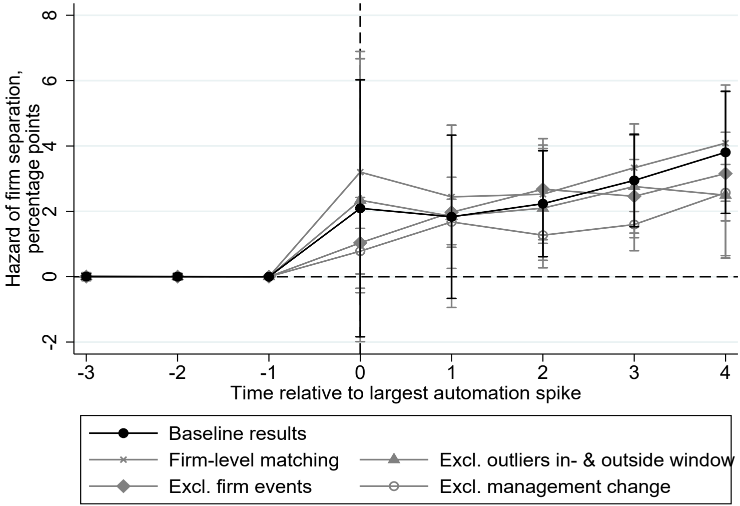

Robustness to spike definition: Firm separation

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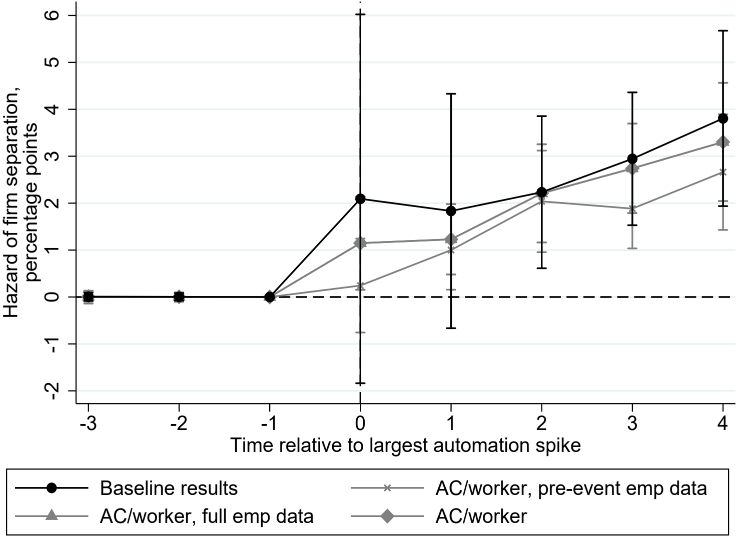

Robustness to model spec.: Firm separation

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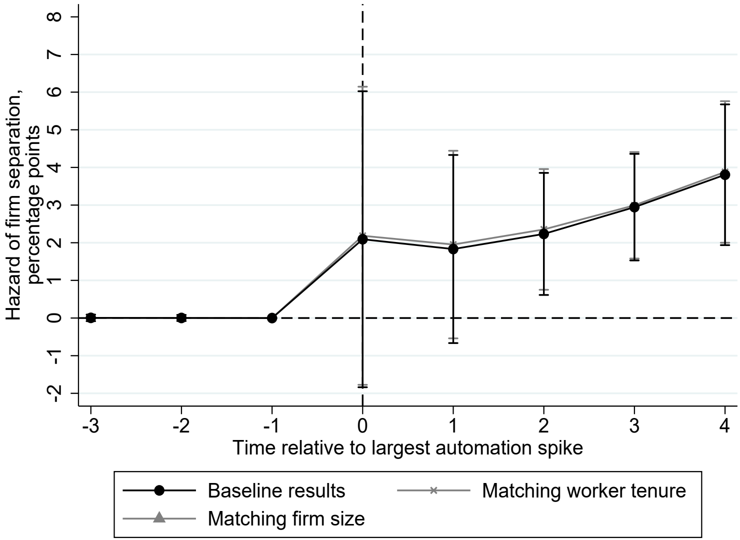

Non-employment estimates, randomization test

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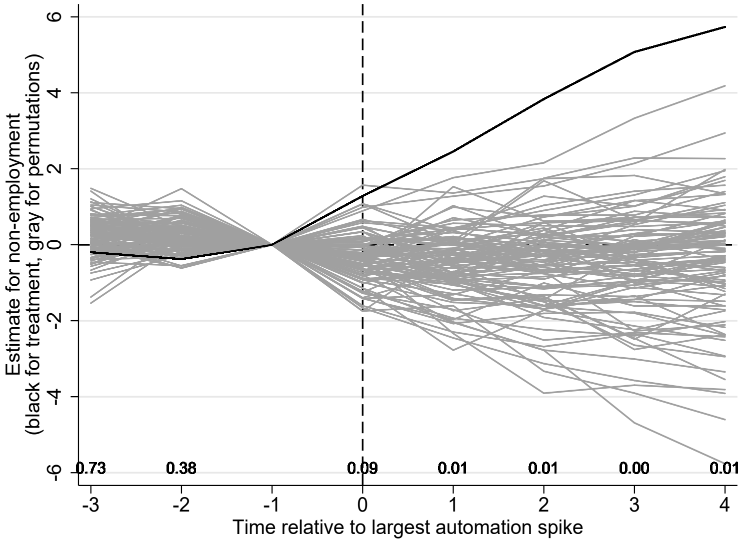

Daily wage estimates, randomization test

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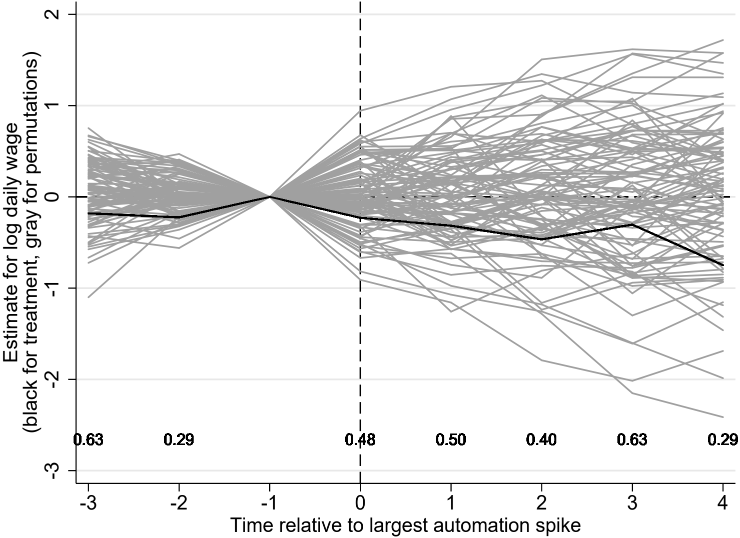

Appendix: Further estimates

Annual total benefit income, levels

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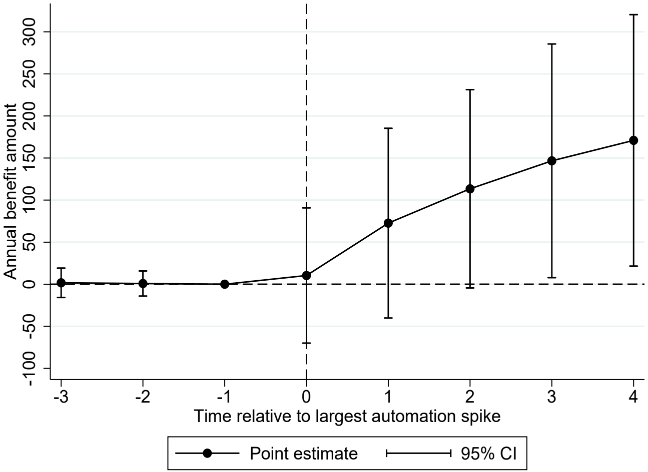

Annual benefit income for CG incumbents is EUR 186 in t=0 and EUR 781 in t=4

Annual benefit income split

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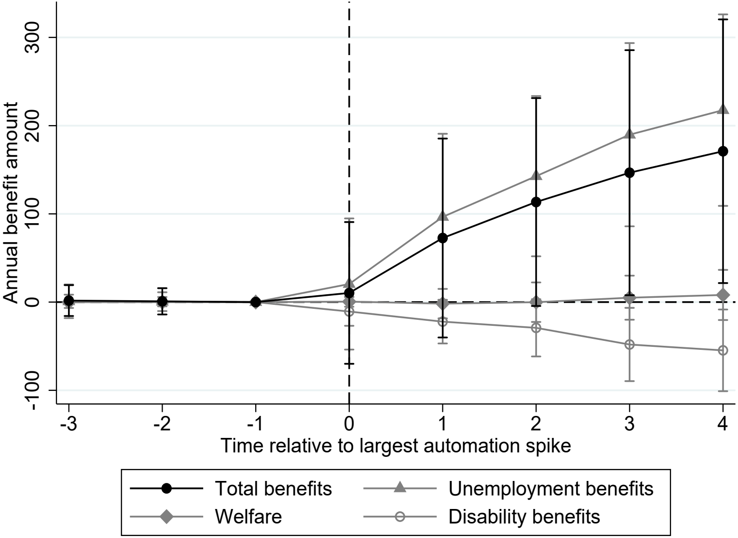

Probability of switching industries

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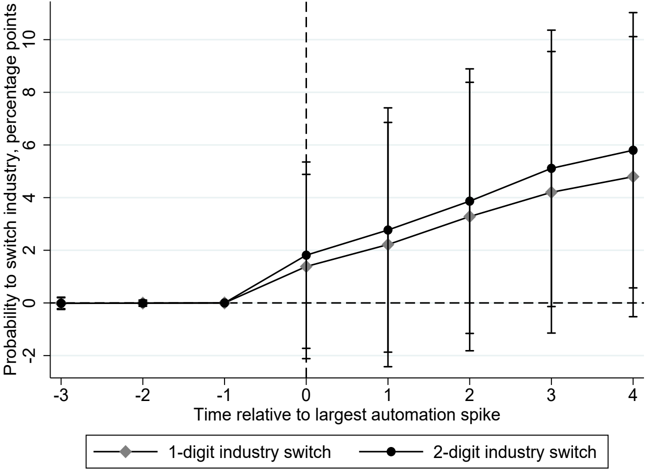

Industry switch probability for CG incumbents is 7% in t=0 and 30% in t=4 (20%↑)

Probability of early retirement

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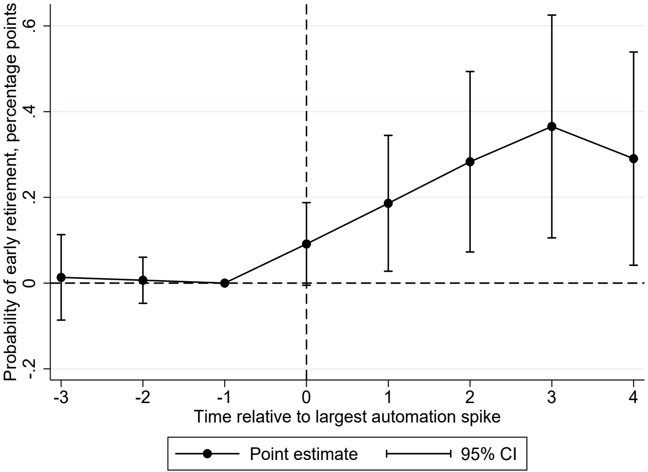

Early retirem. probability for CG incumbents is 0.2% in t=0 and 1.5% in t=4 (18%↑)

Heterogeneity in average annual wage impact

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(1) Age	
Age <30 (ref)	-1.84
	(3.19)
Deviations from reference group for:	
Age 30-39	-0.24
	(3.73)
Age 40-49	0.42
	(3.60)
Age 50+	-1.20
	(3.94)
(2) Firm size	
500+ employees (ref)	-1.53
	(1.35)
Deviations from reference group for:	
200-499 employees	1.21
	(1.77)
100-199 employees	-2.19
	(1.77)
50-99 employees	0.17
	(1.57)
20-49 employees	-2.18
	(1.46)
1-19 employees	-2.06
	(1.52)

(3) Gender	
Male (ref)	-1.52***
	(0.57)
Deviations from reference group for:	
Female	-1.39
	(0.97)
(4) Sector	
Manufacturing (ref)	-1.98**
	(0.99)
Deviations from reference group for:	
Construction	1.05
	(1.73)
Wholesale & retail trade	-2.23
	(1.51)
Transportation & storage	0.71
	(1.79)
Accommodation & food serving	4.57**
	(2.32)
Information and communication	-0.25
	(1.76)
Prof'l, scientific, & techn'l act's	-0.24
	(1.80)
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*	Bottom quartile (ref)	-1.06
	(1.20)		(1.26)
Deviations from reference group for:		*Deviations from reference group for:*	
Second quartile	0.17	Second quartile	-1.37
	(1.10)		(1.12)
Third quartile	0.48	Third quartile	-0.75
	(1.39)		(1.31)
Top quartile	0.09	Top quartile	-1.62
	(1.65)		(1.56)

Annual earnings for incumbents vs. recent hires

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