No Teens, No Tech: How Shortages of Young Workers Hinder Firm Technology Investments

Cäcilia Lipowski
ifo institute & ZEW Mannheim

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- Lack of evidence; Identification challenging

This Paper

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- Finding: Trainee shortages **decrease** firm technology investments
- Mechanism: New technologies require **new skills**, in which young workers have comparative advantage

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   - Mechanism via tech investments

Setting + Reform

Vocational Training (VT) in Germany

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- Vocational training follows school graduation:
  - basic/intermediate track (9/10y) $\Rightarrow$ VT ("low-educ. trainees")
  - upper track (12/13y) $\Rightarrow$ $\approx$ 1/3 VT ("highly educated trainees")

Reform: Missing school graduates

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⇒ Should reduce stock of highly educated trainees 2002–2004 by 1/3

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- 12% of hires; 13% of young workers (<30years)

Data

Yearly firm panel data

LIAB: Representative establishment panel survey

+ linked administrative employer-employee data

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- Employment of highly educated trainees + investments at firm level

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⇒ East Germany, 1997–2006: **2,303 firms (578 training firms)**

⇒ ≈ **3.9% of East German workforce** each year

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- Log total investments; Investments per worker

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- Organizational change following Battisti et al. (2023)
  - Restructuring of departments
  - Downward shifting of responsibilities
  - Introduction of team work
  - Introduction of units carrying out own cost and result calculations

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⇒ Likely digital technologies, software, computer-controlled machines

Identification

DiD Event Study

Inference

$$Y_{jt} = \sum_{t=1997, t \neq 2000}^{t=2006} \alpha_t (\text{Treated}_j \times \text{Year}_t) + \psi_t + \phi_j + \epsilon_{jt}$$

- Treated: Saxony-Anhalt, Mecklenburg-Western Pomerania
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  - Among *non*-training firms as falsification test

Firm matching ▸ Balancing

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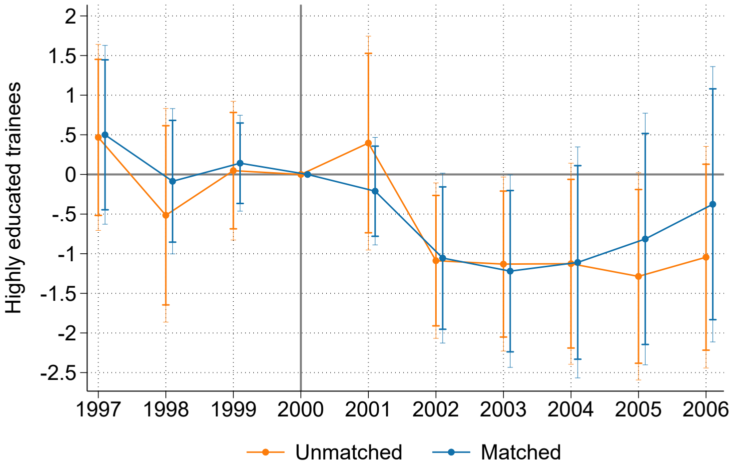
$\Rightarrow$ Little differences

Bite of the reform

Employment of highly educated trainees drops by ≈ 20%



Firms do not compensate highly educated missing trainees ▸ More

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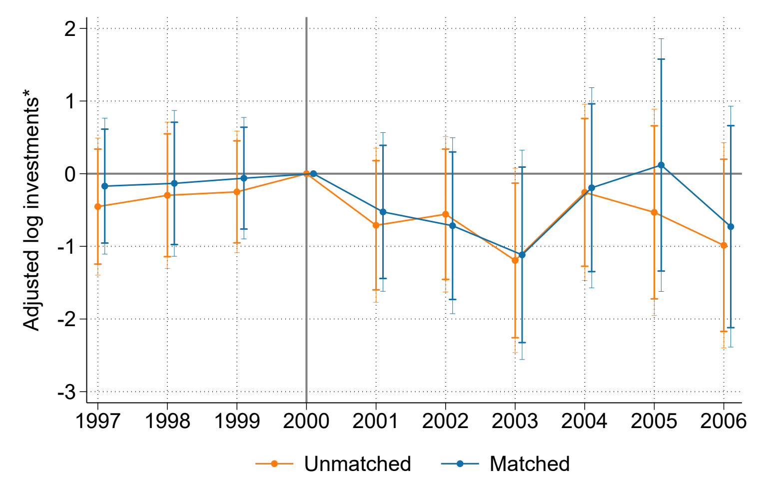
Effect on tech investments

Investments decline



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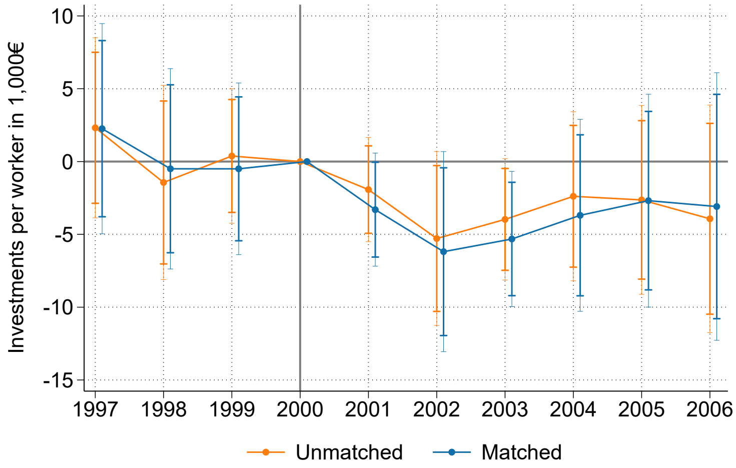

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  - Fisher randomization tests, Wild cluster t-bootstrap ▸ Cluster t ▸ Fisher

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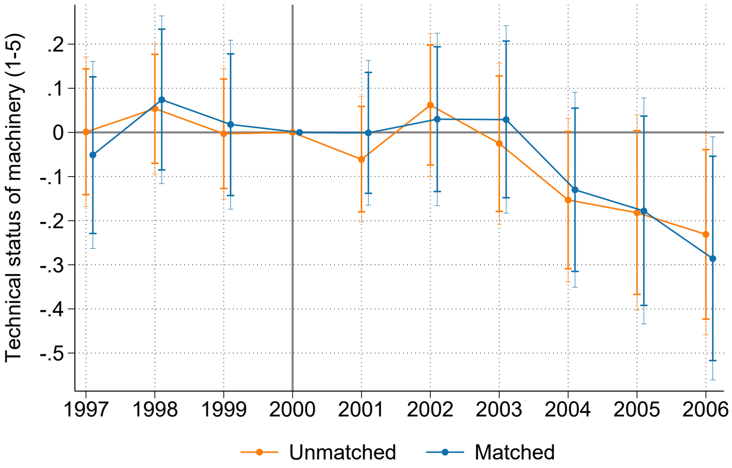
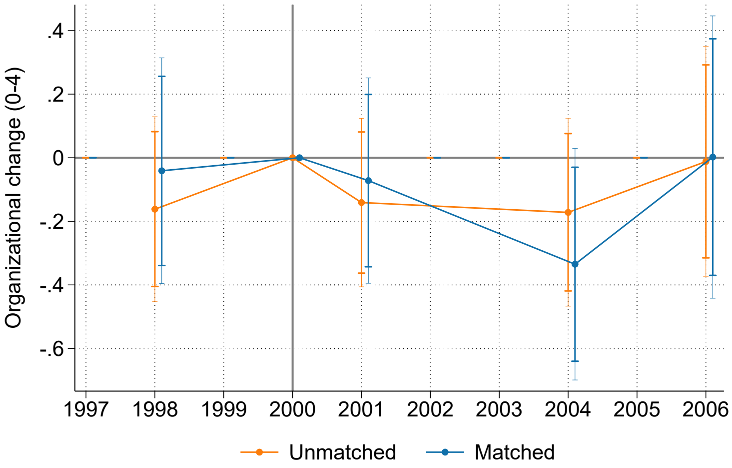


Firm-level organizational change slows down



Mechanism

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⇒ Firms endogenously "make" trainees complements with technology

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3. Young workers use more new technologies ⇒ Employee survey ▸ More
   - Finding holds for all education groups ⇒ External validity

Alternative channels

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✗ Cannot explain why marginally older workers cannot compensate

Conclusion

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2. New skills demanded by new technologies are highly relevant
3. Retraining incumbents is costly

$\Rightarrow$ 2+3: strong vintage effects: worker cohorts posses different skills

Appendix

References

Acemoglu, D. (2002). Directed technical change. The Review of Economic Studies, 69(4), 781–809.

Autor, D., Chin, C., Salomons, A., & Seegmiller, B. (2024). New frontiers: The origins and content of new work, 1940–2018. The Quarterly Journal of Economics, qjae008.

Battisti, M., Dustmann, C., & Schönber, U. (2023). Technological and organizational change and the careers of workers. Journal of the European Economic Association, 21(4), 1551—1594.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. The Review of Economics and Statistics, 90(3), 414–427.

Carneiro, P., Liu, K., & Salvanes, K. G. (2022). The supply of skill and endogenous technical change: evidence from a college expansion reform. Journal of the European Economic Association.

Cavounidis, C., & Lang, K. (2020). Ben-porath meets lazear: Microfoundations for dynamic skill formation. Journal of Political Economy, 128(4), 1405–1435.

References ii

Chari, V. V., & Hopenhayn, H. (1991). Vintage human capital, growth, and the diffusion of new technology. Journal of Political Economy, 99(6), 1142–1165.

Dechezleprêtre, A., Hémous, D., Olsen, M., & Zanella, C. (2019). Automating labor: evidence from firm-level patent data. Available at SSRN 3508783.

Deming, D. J., & Noray, K. (2020). Earnings dynamics, changing job skills, and stem careers. The Quarterly Journal of Economics, 135(4), 1965–2005.

Le Barbanchon, T., Ronchi, M., & Sauvagnat, J. (2023). Hiring frictions and firms' growth. Available at SSRN 4105264.

Lewis, E. (2011). Immigration, skill mix, and capital skill complementarity. The Quarterly Journal of Economics, 126(2), 1029–1069.

Lipowski, C., Salomons, A., & Zierahn-Weilage, U. (2024). Expertise at work: New technologies, new skills, and worker impacts. ZEW-Centre for European Economic Research Discussion Paper, 24-044.

MacDonald, G., & Weisbach, M. S. (2004). The economics of has-beens. Journal of Political Economy, 112(S1), S289–S310.

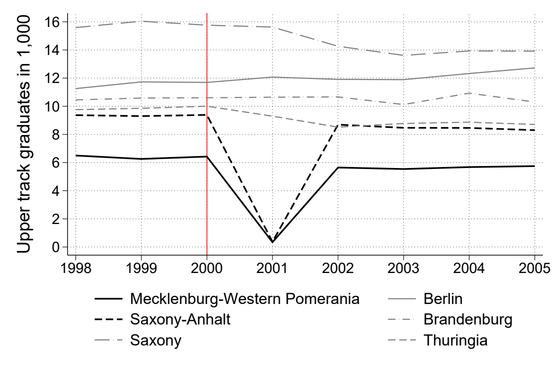
Roth, J., Sant'Anna, P. H., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. Journal of Econometrics, 235(2), 2218–2244.

Sauvagnat, J., & Schivardi, F. (2024). Are executives in short supply? Evidence from death events. Review of Economic Studies, 91(1), 519–559.

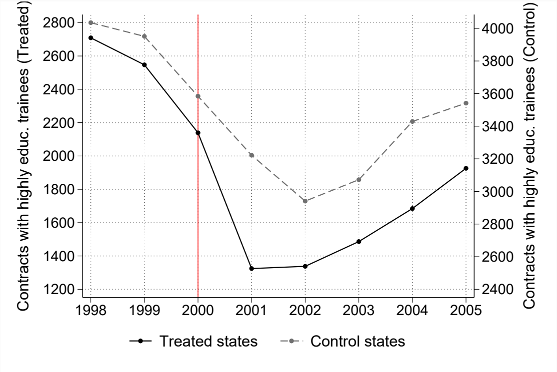
Descriptives of the reform

Reform

(A) School graduates by state



(B) New training contracts



Notes: Official statistics, own calculations.

Balancing table

Back

	Unmatched			Matched		
	Treated	Treated - Control	SE	Treated	Treated - Control	SE
	(1)	(2)	(3)	(4)	(5)	(6)
			A. Targeted variables			
Δ log employment	-0.26	-0.10	0.07	-0.17	-0.03	0.03
Log employment	4.93	-0.35	0.13**	5.06	-0.17	0.13
Share highly educated trainees	2.86	-1.83	3.52	2.57	0.36	0.36
			B. Non-targeted variables			
# highly educated trainees	3.94	-3.33	1.86*	4.53	-0.60	0.87
Trainee wage	21.75	0.15	0.84	20.03	-0.43	0.55
Adjusted log investments	11.42	-1.15	0.42**	12.65	-0.34	0.48
Inv. per worker in €1,000	17.46	-0.26	3.17	20.82	0.74	3.50
Technical status	3.95	0.05	0.06	3.95	0.04	0.07
Organizational changes	1.15	-0.13	0.11	1.13	0.02	0.11
Number of firms	578			393		

Notes: Training firms only. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Inference

◂ Back

- Problem: Small number of clusters (=states)

- S1 – Cluster at firm level: Assume state-level shocks relatively small; remaining uncertainty from sampling of firms (Roth et al., 2023)
- S2 – Wild cluster t-bootstraps (Cameron et al., 2008)
- S3 – Fisher randomization tests: T-statistic for actual treatment assignment $\gg$ all permutation assignments (Roth et al., 2023)

Firms do not compensate highly educated missing trainees

Back

	Log wage highly educ. trainees (1)	# low-educ. trainees (2)	# highly educ. commuting trainees (3)	Log highly educ. VT employment (4)	Log wages educ. VT employment (5)	Trainee retention rate (6)	Internal retraining (7)
				A. All training firms (Unmatched)			
Treat × Post	-0.00	-0.90	2.46	0.01	-0.02	-0.06	-0.27*
	(0.03)	(1.77)	(3.18)	(0.08)	(0.02)	(0.04)	(0.16)
Mean dep. variable	3.02	10.06	2.83	2.18	4.29	0.65	0.47
N	2252	3322	1429	3083	3082	3150	1618
				B. Matched training firms			
Treat × Post	0.01	-1.65	2.04	0.03	-0.02	-0.09**	-0.09
	(0.03)	(1.76)	(2.87)	(0.09)	(0.03)	(0.04)	(0.07)
Mean dep. variable	3.03	9.72	2.93	2.25	4.31	0.64	0.50
N	2198	3182	1564	3032	3031	3035	1586

Notes: Baseline: Treated × Pre. Pre: 1997–2000. Post: 2002–2004.

Additional evidence

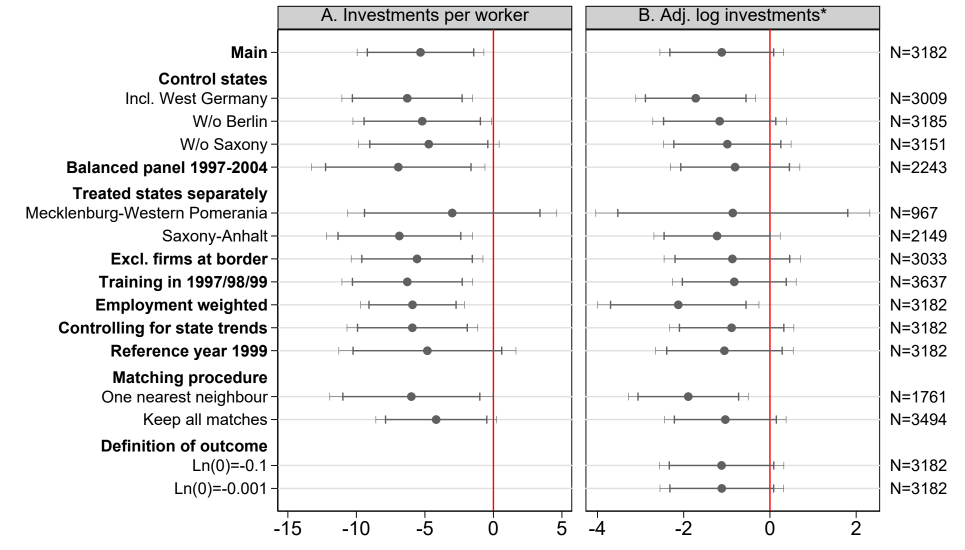
Back

	Log(K) (1)	Any inv. (0/1) (2)	Log(Inv.) (3)	Large inv. (1/0) (4)
	A. All training firms (Unmatched)			
Treat × Post	-0.07	-0.02	-0.16	-0.11**
	(0.05)	(0.04)	(0.15)	(0.05)
Mean dep. variable	10.18	0.90	13.98	0.33
N	3155	3308	2843	2843
	B. Matched training firms			
Treat × Post	-0.10*	-0.03	-0.24	-0.16***
	(0.06)	(0.04)	(0.16)	(0.05)
Mean dep. variable	10.04	0.89	13.82	0.30
N	3064	3176	2809	2809

Notes:

Robustness

◂ Back



Robustness ◂ Back

Notes: Event study coefficients and 90% and 95% confidence bands of the term $\mathrm{Treat} \times 2003$. Panel A using investments per worker in €1,000 as outcome; Panel B using adjusted log investments as outcome. Standard errors clustered at the firm level. Among pre-treatment training firms only. N indicates the number of observations in the respective estimation. *Main:* Main specification. *Control states:* Additionally including all West German training firms as control firms, or dropping Berlin or Saxony from the set of control firms. *Balanced panel 1997-2004:* Sample restricted to firms observed in each year between 1997 and 2004. *Treated states separately:* Only using treated firms from one treated state and dropping firms from the other treated state. *Excl. firms at border:* Dropping those 10% of firms with the highest 1999 cross-state commuter share of workers with vocational training. *Training in 1997/98/99:* Training firms defined as those with at least one highly educated trainee in 1997, 1998, or 1999 instead of 1997 and 1998 only. *Employment weighted:* Observations weighted by firms' initial employment size in 1997. *Controlling for state trends:* Additionally controlling for linear state-specific time trends. *Reference year 1999:* Using 1999 instead of 2000 as reference year. *Matching procedure:* Using only the nearest neighbor instead of the three nearest neighbors as control firms, and keeping all matches instead of discarding the furthest 10% of all matches. *Definition of outcome:* Assigning $log(0) - 0.1$, and $log(0) - 0.001$ instead of $log(0) - 0.01$.

Falsification test among non-training firms

Back

	Adj. log investments		Inv. per worker	
	Training (1)	Non-training (2)	Training (3)	Non-training (4)
Treat $\times$ Post	-0.81 (0.57)	-0.25 (0.33)	-6.11* (3.13)	-2.11 (1.33)
Mean dep. variable	12.28	8.75	15.81	9.79
N	3322	9791	3322	9791

Firm-level treatment intensity – IV regression

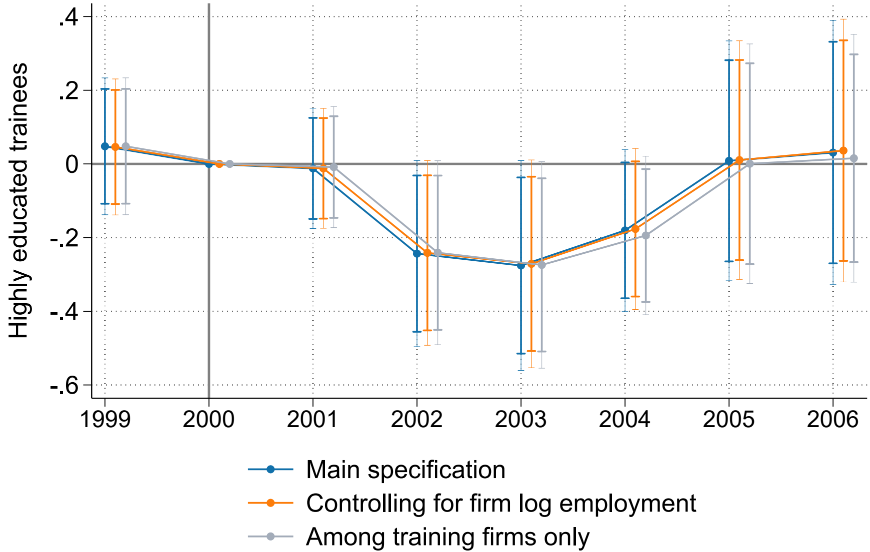
- *Do more affected firms reduce investments more?*

$$\mathrm{Inv}_{jbt} = N_{jbt}^{\mathrm{Trainee}} + \psi_t + \pi_j + \epsilon_{jt}$$

- Firm selection into trainee employment!
  $\Rightarrow$ Predict $N_{jt}^{\mathrm{Trainee}}$ with Bartik IV: reform (*shift*) $\times$ **firm** initial trainee employment (*share*)

$$N_{jbt}^{\mathrm{Trainee}} = \sum_{t=1999, t\neq 2000}^{2005} \gamma_t \left(N_{j,1998}^{\mathrm{Trainee}} \times \mathrm{Treated}_{b(j)} \times \mathrm{Year}_t \right) + \psi_t + \pi_j + \epsilon_{jbt}$$

1st stage: Exposed firms reduce trainee employment more



2nd stage: Exposed firms cut investments more ◂ Back1 ◂ Back2

	Inv. per worker (1)	Adj. log inv.* (2)	Log inv. (3)	Log(K) (4)
		A. Main specification		
N^{Trainee}	0.93*	-0.09	0.04**	0.02**
	(0.53)	(0.06)	(0.02)	(0.01)
F-Stat	15.26	15.26	16.40	16.58
		B. Controlling for firm log employment		
N^{Trainee}	0.92*	-0.09	0.04**	0.02**
	(0.54)	(0.06)	(0.02)	(0.01)
F-Stat	15.41	15.41	16.71	16.78
N	7,037	7,037	5,207	6,737
		C. Among training firms only		
N^{Trainee}	0.61	0.02	0.04*	0.01**
	(0.47)	(0.05)	(0.02)	(0.01)
F-Stat	13.90	13.90	13.43	15.52
N	1,579	1,579	1,349	1,529

Notes: † – For data availability reasons, variable included for the years 2000, 2001, and 2004. F-Stat gives the robust Kleibergen-Paap Wald rk F statistic. Standard errors clustered at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Investment intensity effect $\gg$ firm size effect ◂ Back

Do investments decrease because firms shrink?

Investment intensity effect ≫ firm size effect Back

Do investments decrease because firms shrink?

- Decompose effect in Δ firm size and Δ investments intensity

$$\Delta\Delta LogInv = \Delta\Delta Log(N) + \Delta\Delta Log\left(\frac{Inv}{N}\right)$$

Investment intensity effect $\gg$ firm size effect Back

Do investments decrease because firms shrink?

- Decompose effect in Δ firm size and Δ investments intensity

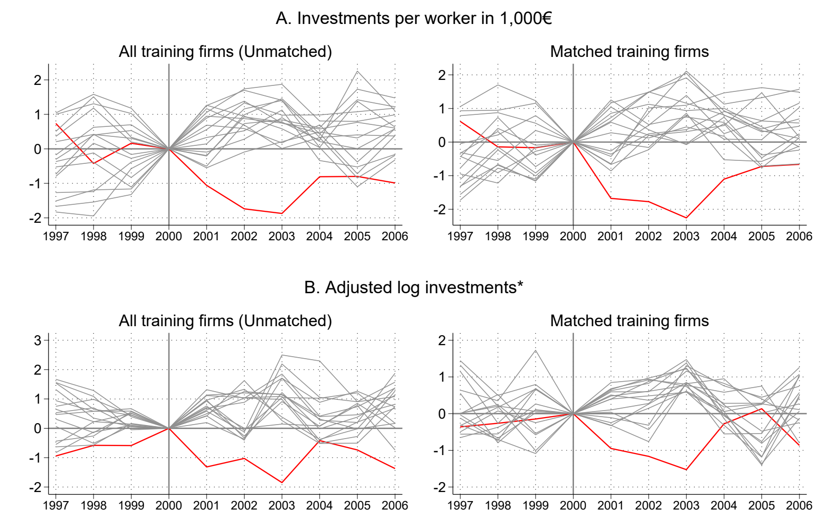
$$\Delta\Delta LogInv = \Delta\Delta Log(N) + \Delta\Delta Log\left(\frac{Inv}{N}\right)$$

$\Rightarrow$ 88-100% of investment drop due to reduced investments per worker

Permutation test – East Germany

Back1 Back2

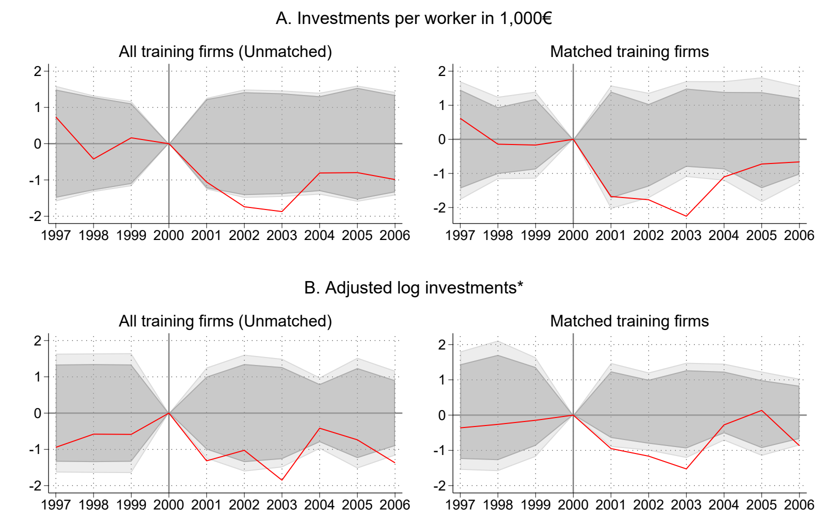
T-statistics



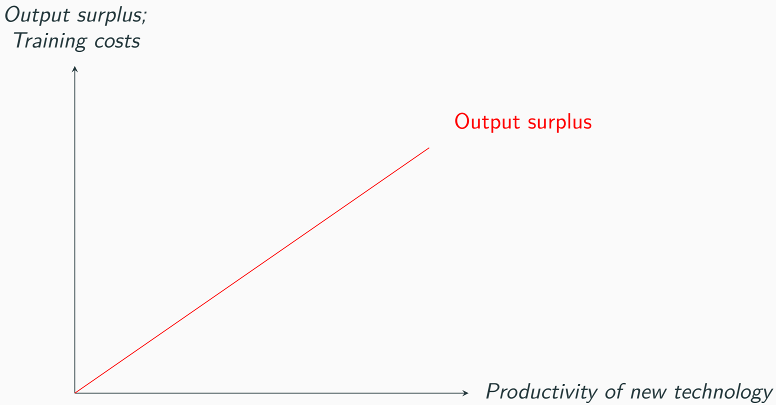
Permutation test – West Germany

Back1 Back2

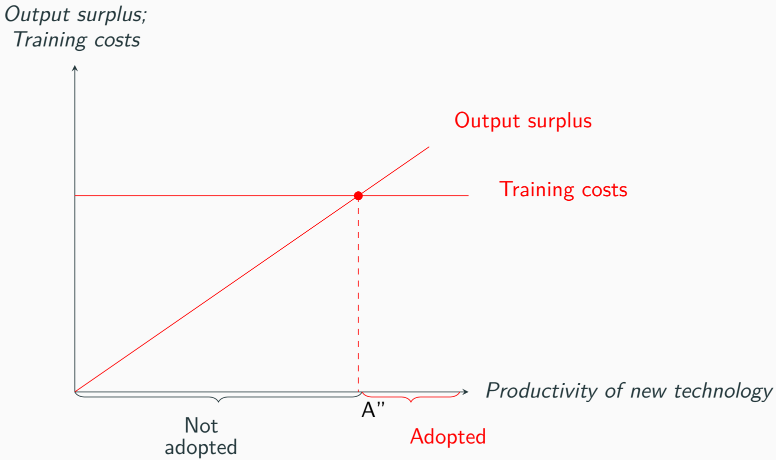
T-statistics



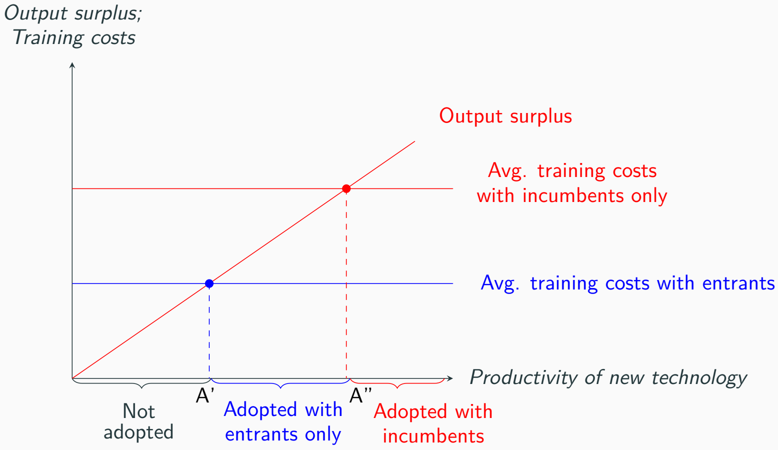
Profits vs. costs of technology adoption



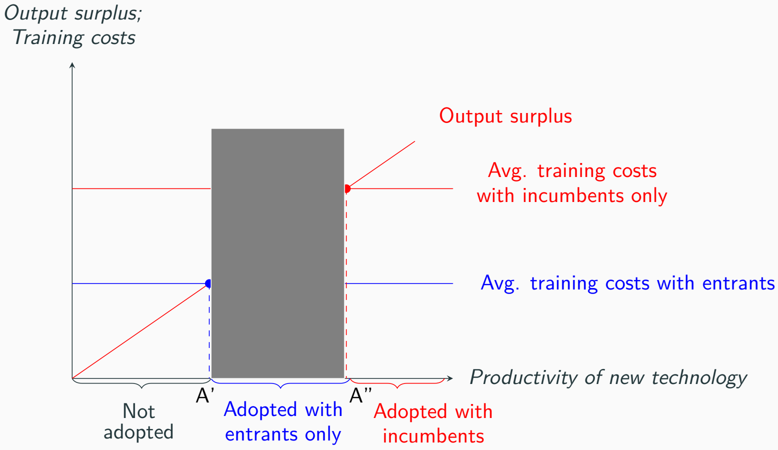
Profits vs. costs of technology adoption



Profits vs. costs of technology adoption



Scarcity of entrants impedes technology adoption



Setting

Production function:

$$Y_{jt} = \sum_{\tau=0}^{\mathcal{T}} A_\tau L_{jt\tau}$$

with final good Y, periods $t = 1, 2$, firms j, labor L_τ, production technologies τ with productivities A_τ

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- Assumption: each technology-vintage requires specific skills

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Start of period: cohort of workers L_0 with A_0

Setting

Production function:

$$Y_{jt} = \sum_{\tau=0}^{\mathcal{T}} A_\tau L_{jt\tau}$$

with final good Y, periods $t = 1, 2$, firms j, labor L_τ, production technologies τ with productivities A_τ

- Assumption: each technology-vintage requires specific skills

Start of period: cohort of workers L_0 with A_0 + new technology τ

Firm maximization problem ◂ Back

Firms maximize profits, deciding whether to adopt + train:

$$\max_{\sum_{\tau_0=0}^{\mathcal{T}-1}} \Delta Y_{j\tau} - \Delta C_{j\tau}$$

Firm maximization problem

Back

Firms maximize profits, deciding whether to adopt + train:

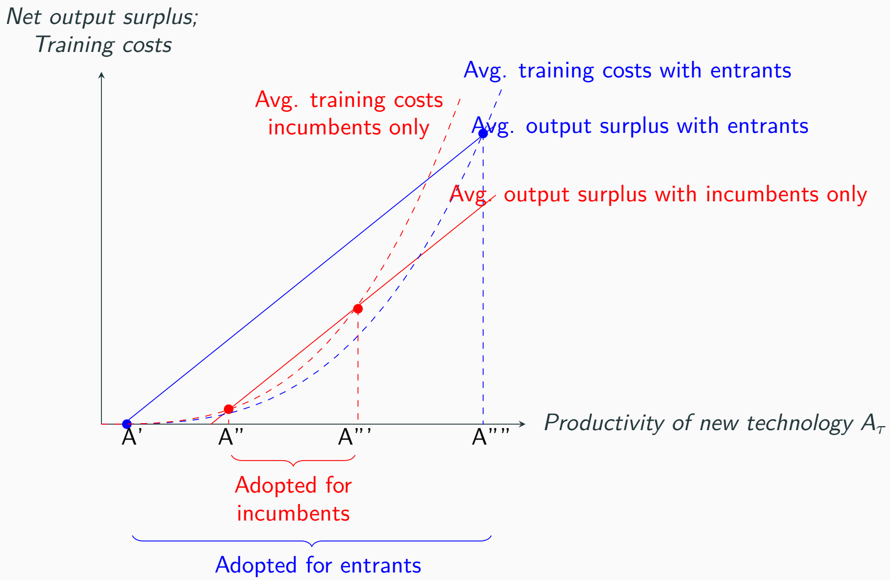
$$\max_{\sum_{\tau_0=0}^{\mathcal{T}-1}} \Delta Y_{j\tau} - \Delta C_{j\tau}$$

Capital adjustment costs:

$$\Delta C_{j\tau} = A_{\tau_0} L_{jt\tau_0}$$

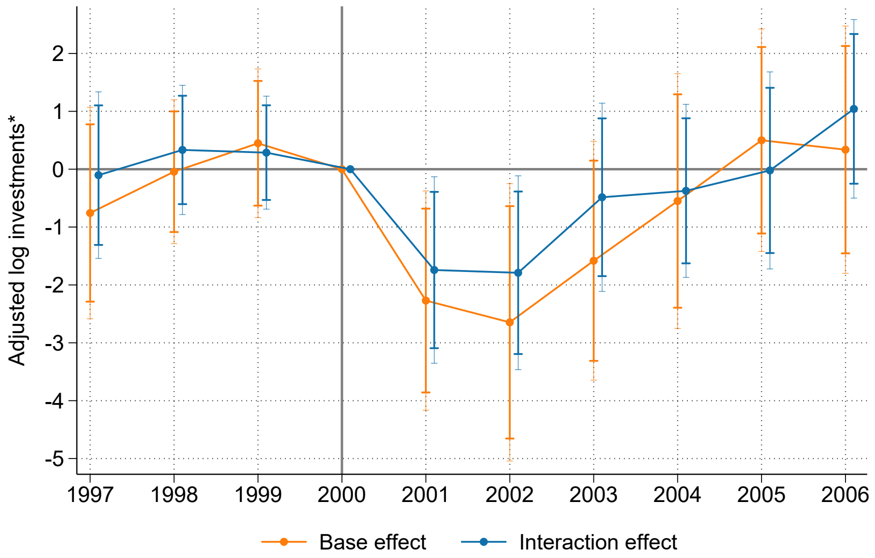
Increasing and convex capital adjustment costs

Back



Investments drop relates to vintage-specific skills

Back



Firms need trainees to adapt to technological change

◂ Back

Use of vocational training according to firm survey

	Applies	Does not apply
Ensures supply of new skills and knowledge	51%	16%
Improves adaptability to technical change	46%	19%
Enhances innovative capabilities	51%	18%

Notes: Based on the BIBB-Cost-Benefit Survey 2000. Firms in East Germany only. On a scale from 1 ("Does not apply at all") to 5 ("Fully applies"). Applies: categories 4+5. Does not apply: Categories 1+2. Using representative survey weights. N=553.

Young workers use new working tools more/earlier ◂ Back

Outcome: Use of computer-controlled machines (0/100)

	Main results		External validity across education groups			
			Low-educ. with VT	Highly educ. with VT	No education	Tertiary educated
	(1)	(2)	(3)	(4)	(5)	(6)
Reference category: 18-29 years						
30+	-5.60***	-4.40***	-5.00***	-3.10**	-4.40***	-2.18
	(0.79)	(0.69)	(0.98)	(1.51)	(0.69)	(1.53)
Controls		X	X	X	X	X
Mean dep. variables	34.90	34.90	39.91	29.95	34.90	24.35
N	45,488	45,488	28,769	8,540	45,488	11,281

Notes: Based on the BIBB-BAuA Qualification and Career Survey. 1999, 2006 and 2012 waves. All regressions control for dummies for the respective survey wave. Controls include gender, occupations (353), industries (17). Heteroscedasticity-robust standard errors. Columns 1 and 2: Among workers with completed vocational training. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.