Integrators:
The Firm Boundaries of Capital-Skill Complementarity

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NBER SI 2026 Labor Studies

The views expressed in this presentation are those of the authors and do not necessarily reflect the views of the National Bank of Belgium.

This Paper

Puzzle

- Capital-skill complementarity is a cornerstone of a vast literature on technology and labor market inequality (Griliches, 1969; Goldin and Katz, 1998; Krusell et al., 2000)
- Yet recent firm-level evidence has been elusive: investing firms expand employment but do not alter their skill mix (Hirvonen et al., 2025; Aghion et al., 2025; Curtis et al., 2023)

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Hypothesis

- Skills most complementary to new machinery are often not hired *in-house*

Case in Point: Robot Integrators

Robot integration represents 2/3 of robot costs (IFR, 2021)

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Robot integrators grew 300% in the last decade (RIA, 2020)

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Strategy

1. Link firm data on capital investments, B2B transactions, and worker skills in Belgium
2. Study employment of skills around investment events
   → In-house employment vs. outsourced labor services
3. Test why firms outsource these skills
4. Quantify aggregate implications

Conceptual Framework

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Capital investment

$$K_{jt+1} = (1-\delta)K_{jt} + G_{jt}(I_{jt}, S^I_{jt}, U^I_{jt})$$

Production

$$Y_{jt} = F_{jt}(K_{jt}, S^P_{jt}, U^P_{jt})$$

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Investment-skill complementarity of Goldin & Katz (1998)

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▸ Model Predictions

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for each $\mathbf{L} = \{S^P, U^P, S^I, U^I\}$.

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Fixed & adjustment costs of hiring tech-complementary skills (Abraham & Taylor, 1996)

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(we test these)

Data & Empirical Strategy

Data & Measurement

Link comprehensive firm-level data in Belgium (2003 to 2021) on

- Capital and investments (annual accounts)
- Firm-to-firm transactions (VAT register)
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External employment of firm j

$$\mathbf{L}_{jt}^{O} = \sum_{i} \frac{X_{ijt}}{X_{it}} \mathbf{L}_{it}^{H}$$

where

- X_{ijt} is sales of firm i to firm j
- X_{it} is total sales of firm i
- $\mathbf{L}_{it}^{H}$ is in-house employment of i

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Firm Employment (Year of Investment Spike)

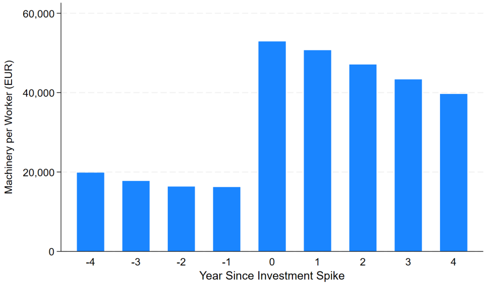
	Total (FTE)	Share of Total (%)			
		High STEM	High Non-STEM	Low STEM	Low Non-STEM
In-House Employment	39.7	5.0%	14.2%	25.5%	55.3%
External Employment	22.9	6.7%	15.1%	26.8%	51.4%
Machine Suppliers	3.6	13.9%	15.4%	35.9%	34.8%

Empirical Strategy

Investment spikes design (Bessen et al, 2025; ...)

- Leverage lumpy capital adjustments (Cooper and Haltiwanger, 2006)
- Study employment before/after spikes (DiD vs. non-spiking firms)

Machinery Stock per Worker around Spike



$$\text{Spike}_{jt} = \mathbf{1}[i_{jt} \geq i_{P90}] \quad \text{with}$$

$$i_{jt} = \frac{\Delta \text{Machinery}_{jt}}{\frac{1}{2}(L_{jt} + L_{jt-1})}, \quad i_{P90} = 17{,}115 \text{ €}$$

Empirical Strategy: Identification

Threat: investment spikes may coincide with other shocks that shift the skill mix

Validity checks

- Validated against quasi-experiments (Aghion et al., 2025; Hirvonen et al., 2025)
- Pre-trends: spiking/non-spiking firms balanced before the spike ‣ Link
- Controlling for sales growth leaves results intact ‣ Link
- Skill bias specific to advanced-technology capital, not investment per se ‣ Link

Empirical Strategy: Estimation

Stacked difference-in-differences (spiking vs. not-yet-spiking, same industry-year)

$$Y_{sjt} = \beta_1 \text{Spike}_{je} + \sum_k \beta_{0k} \mathbf{1}_{\{t=e+k\}} + \sum_{k \neq -2} \beta_{1k} \text{Spike}_{je} \mathbf{1}_{\{t=e+k\}} + \varepsilon_{sjt}$$

β_{1k}: DiD k years after the spike (vs. $k = -2$), estimated separately by skill s

$\rightarrow$ effect of spiking in year e relative to the counterfactual post-spike path

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Outcome Y_{sjt}: *total* (in-house + external) employment by skill s, % of pre-spike

$\rightarrow$ Skill groups s: High/Low $\times$ STEM/Non-STEM

$\rightarrow$ Split total into in-house (H) vs. external (O): $Y^M_{sjt} = L^M_{sjt} / \left(L^H_{sj\mathrm{pre}} + L^O_{sj\mathrm{pre}} \right)$

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Sample: first spikes, 5+ FTE pre-spike; controls = same NACE-3 $\times$ event year; balanced $\pm$4 years

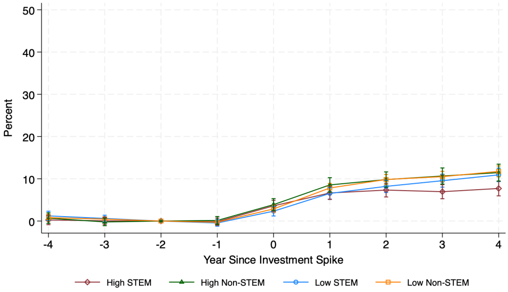
Robust to: spike thresholds, single-spiking treated; later-/never-spiking controls; unbalanced panel

New Machinery and the Demand for Skills

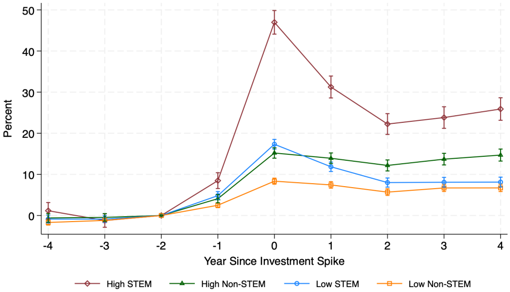
Firm Employment Around Machinery Investment Spikes

Employment as a Share of Total Pre-spike Employment by Skill

In-House



External



Notes: Diff-in-diffs in $Y_{sjt}^M = L_{sjt}^M / (L_{sj\mathrm{pre}}^H + L_{sj\mathrm{pre}}^O)$, $M \in \{H, O\}$, vs. non-spiking firms in same industry-year

Skill Bias from External Suppliers, Not In-house Hires

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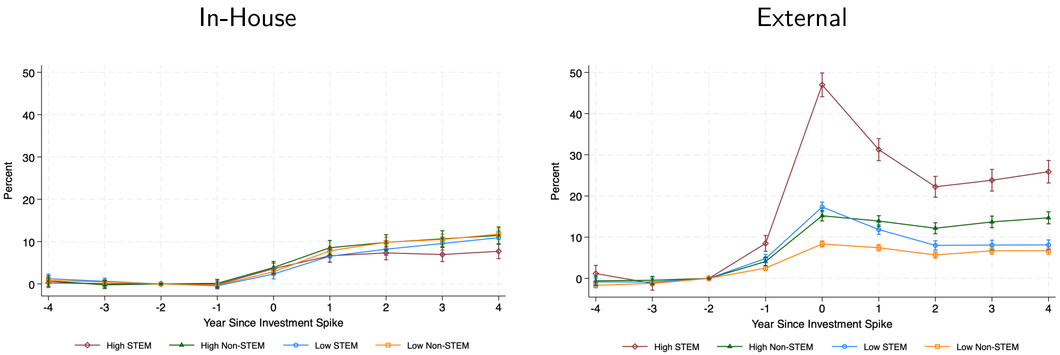

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‣ Drivers of External Skill Bias ‣ Sales Controls ‣ Robustness

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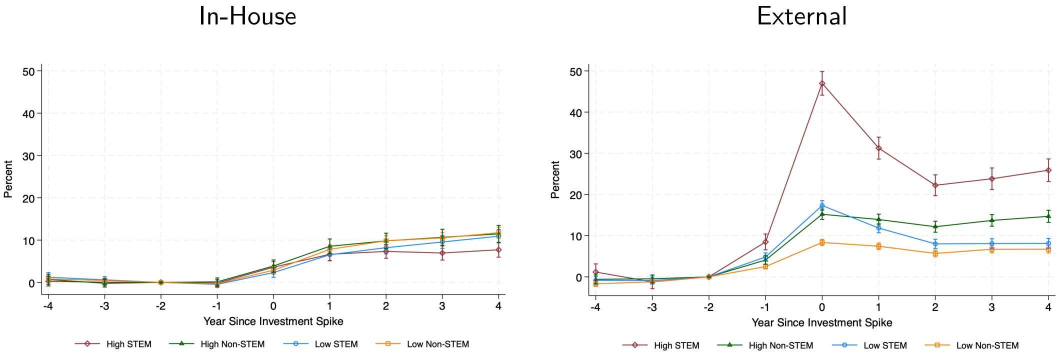

Investment-skill complementarity (Goldin & Katz) followed by capital-skill complementarity (Griliches) — but not hired in-house

External Skill Bias: Machine Suppliers First, Other Industries Later

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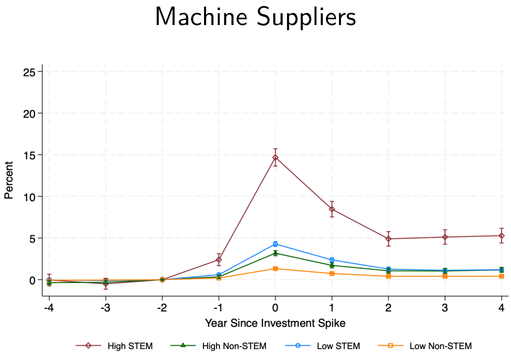

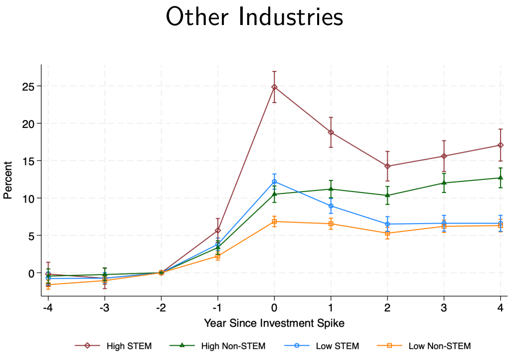

Notes: Diff-in-diff relative to industry average of non-spiking firms.

▸ Industry Codes ▸ Decomposition: Other Industries

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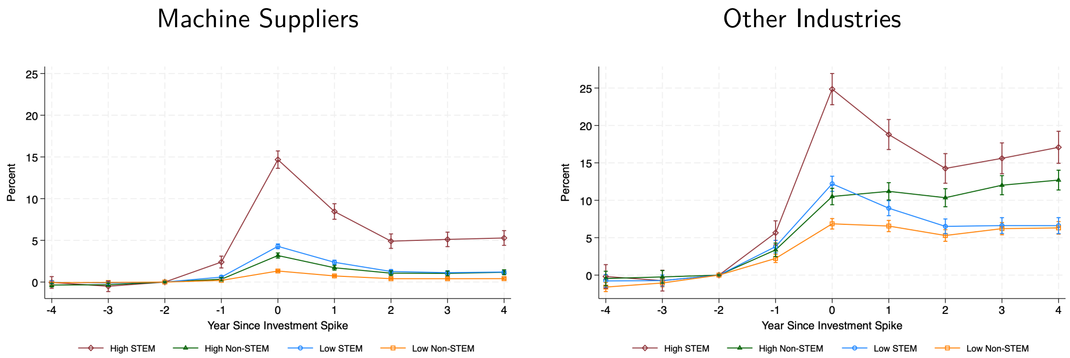

Machine suppliers drive the initial spike; other industries (e.g., software) the longer-run gains

▸ Industry Codes ▸ Decomposition: Other Industries

From Reduced-Form Responses to Substitution Elasticities

Nested CES (Krusell et al., 2000)

$$H = \left[\alpha K^{\rho} + (1-\alpha) L_S^{\rho}\right]^{1/\rho}, \;\; \sigma_{KS} = \tfrac{1}{1-\rho}; \qquad Y = \left[(1-\mu) H^{\eta} + \mu L_U^{\eta}\right]^{1/\eta}, \;\; \sigma_{HU} = \tfrac{1}{1-\eta}$$

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$$\frac{\sigma_{HU}}{\sigma_{KS}} = 1 + \frac{1}{s_K^H} \cdot \frac{\Delta \ln L_S - \Delta \ln L_U}{\Delta \ln K - \Delta \ln L_S} \approx 1 + 3 \cdot \frac{0.29 - 0.17}{0.9 - 0.29} \approx 1.6$$

K: machinery; L_S: high-STEM; L_U: low non-STEM; s_K^H: machinery cost share in inner nest

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Capital-skill complementarity at the firm level,
although more muted than the aggregate ratio of ≈ 2.5 from Krusell et al. (2000)

▸ Derivation & Calibration

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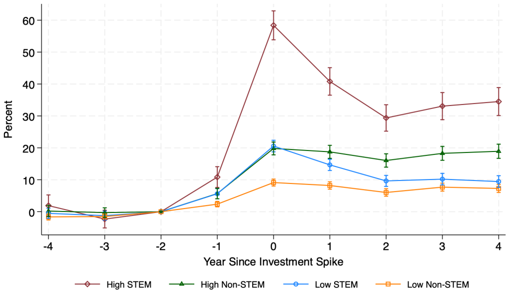
(we aggregate later)

Why Firms Outsource
Capital-Complementary Skills

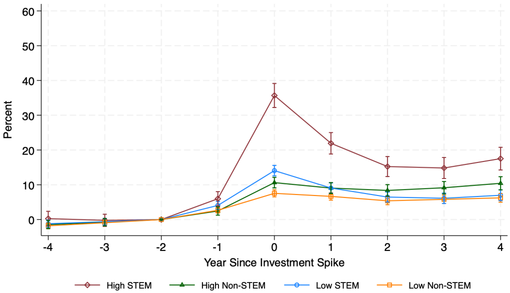
Smaller Firms More Likely to Outsource Machine-Complementary Skills

External Employment as a Share of Total Pre-spike Employment by Skill

Smaller Firms



Larger Firms



Notes: Smaller firms have total pre-spike employment below the median (13.1 FTE).

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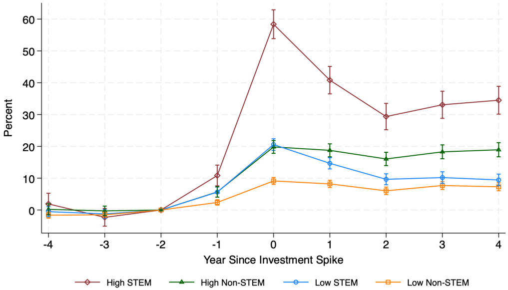

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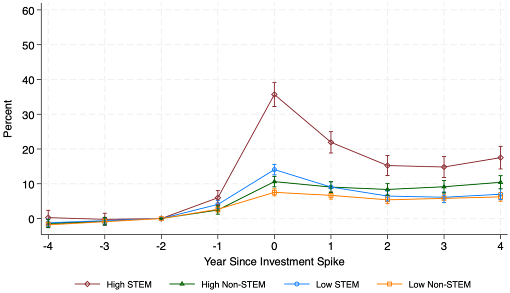
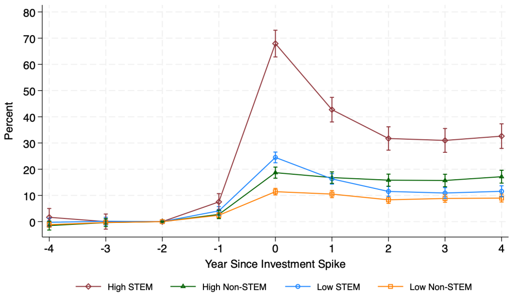


Consistent with scale economies in machine-complementary skills

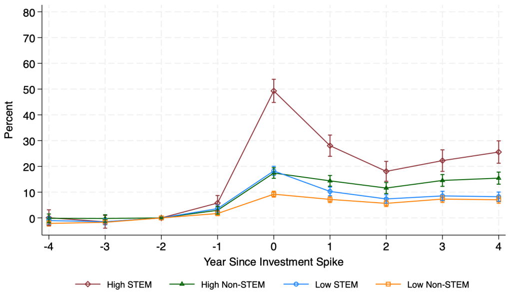
Stronger External Skill Bias from New-Supplier Spikes

External Employment as a Share of Total Pre-spike Employment by Skill

Spikes Driven by New Suppliers



Spikes Driven by Existing Suppliers



Notes: Split by whether the rise in machine-supplier purchases is driven by new or existing suppliers.

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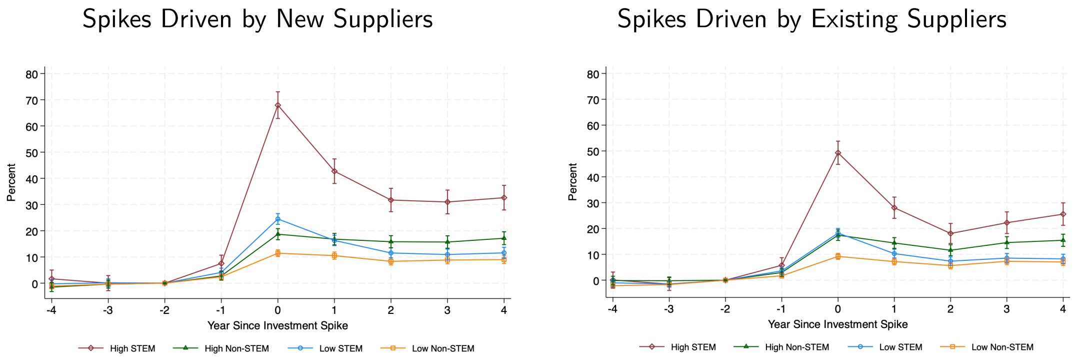
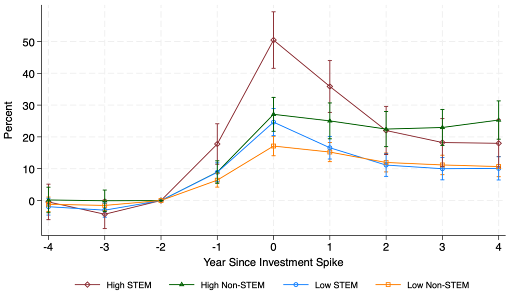


Consistent with skill bias from embodied new technologies (Solow, 1960)

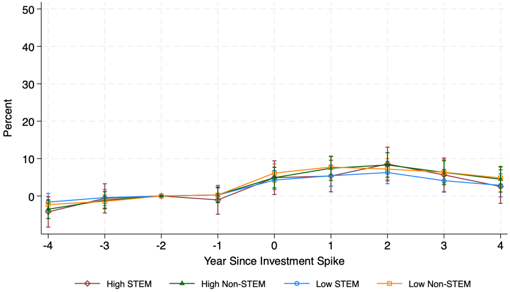
Less Outsourcing of Skills for More-Mature, Less-Lumpy Capital

External Employment as a Share of Total Pre-spike Employment by Type

Building Spikes



Intangibles Spikes



Sample: investment spikes by manufacturing firms.

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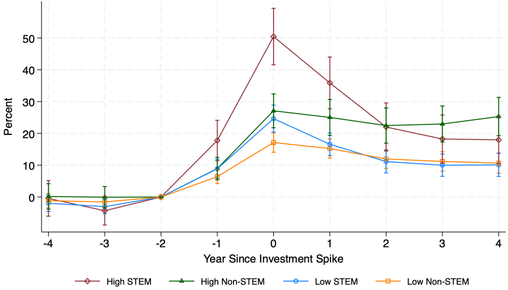

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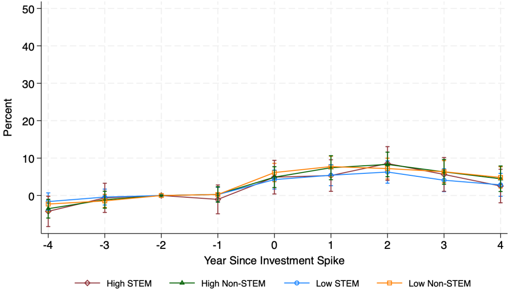

Consistent with embodied new technologies (mature capital)
and hiring/firing costs (lumpy events) driving the external skill bias

Additional Evidence

Why do firms outsource?

- Machinery skill bias pervasive across sectors ‣ Link
- Machine suppliers smooth lumpy, indivisible demand across clients ‣ Link
- Not wage savings: low-wage firms outsource *more*, suppliers pay higher wages ‣ Link

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Can standard approaches capture the external skill bias?

- *Local labor markets miss it*: external skills mostly from outside CZ ‣ Link
- *Sectoral input-output misses it*: shift toward high-STEM suppliers ‣ Link

Aggregate Implications

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Taking stock

- Machinery investments generate high-STEM bias
- Skill bias entirely driven by external suppliers
- Machine integration initially, other industries (e.g., software) eventually

Q: Are these effects big enough to matter for aggregate labor demand?

▸ Details

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Strategy

1. PE Shift: Scale firm-level DiDs with aggregate rise in machinery
2. GE Impact: Convert PE shift using calibrated labor market elasticities

▸ Details

Aggregate Implications

Aggregate Skill Bias of New Machinery

(Diffs to Low Non-STEM in Percentage Points, 2003-2021)

	PE Shift			GE Impact	
	In-House (1)	External (2)	Total (3)	Employment (4)	Skill Premium (5)
High STEM	**-3.7**	**24.2**	**20.5**	**10.2**	**6.8**
– Integration	-0.3	8.0	7.7		
– Production	-3.4	16.2	12.8		

Notes: GE Impact assumes $\varepsilon_s^D = 1.5$ (Katz and Murphy, 1992; Krusell et al., 2000) and $\varepsilon_s^S = \varepsilon_s^D$

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PE shift = **20pp** for high-STEM — entirely from *external* suppliers

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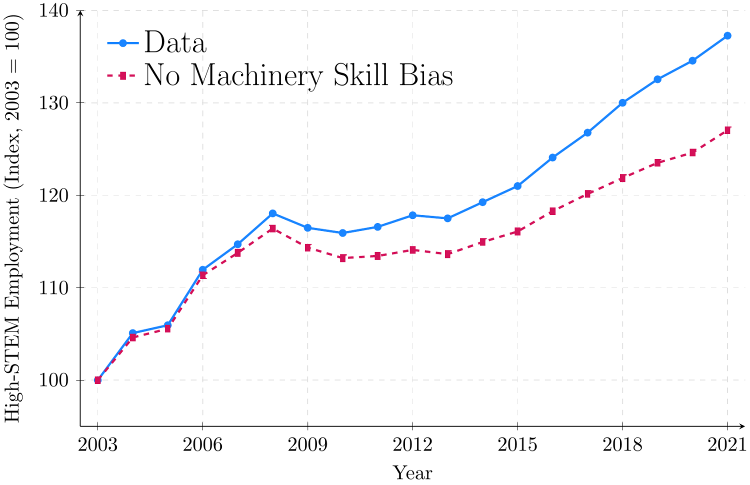
	PE Shift			GE Impact	
	In-House	External	Total	Employment	Skill Premium
	(1)	(2)	(3)	(4)	(5)
High STEM	**-3.7**	**24.2**	**20.5**	**10.2**	**6.8**
– Integration	-0.3	8.0	7.7		
– Production	-3.4	16.2	12.8		

Notes: GE Impact assumes $\varepsilon_s^D = 1.5$ (Katz and Murphy, 1992; Krusell et al., 2000) and $\varepsilon_s^S = \varepsilon_s^D$

Central calibration $\rightarrow$ **10pp employment + 7pp skill-premium growth**

Machinery Skill Bias Accounts for ¼ of the High-STEM Rise



Conclusion

Upshot

Strong evidence for capital-skill (Griliches, 1969; Krusell et al., 2000) and investment-skill complementarity (Goldin and Katz, 1998) ... but not hired in-house

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→ Theory: Central role of external suppliers ("integrators") in technology adoption

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THANK YOU

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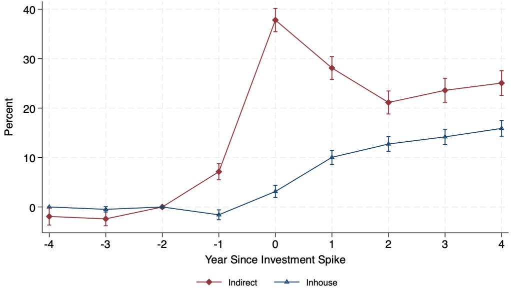
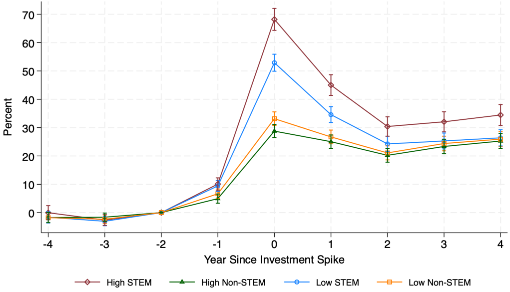
Drivers of External Skill Bias around Machinery Investment Spikes

In-house and External Employment Growth



External Employment of Skills



Notes: Panel (a) in-house and external employment, in percent of pre-spike employment by type. Panel (b) external employment by skill group, in percent of pre-spike external employment by skill.

Return

Which Other Industries Drive the External Skill Bias?

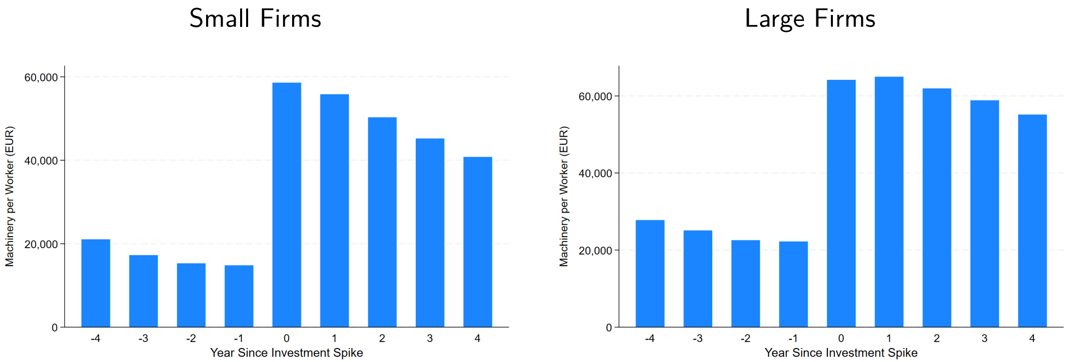
Table: Decomposing the Impact on External Employment through Other Industries

	Pre-Spike Share	Effect on External Employment (Year 4)				Skill Bias
		High STEM	High Non	Low STEM	Low Non	
	(1)	(2)	(3)	(4)	(5)	$\frac{(2)-(5)}{(1)}$
Machine Suppliers	10.51	5.28	1.17	1.20	0.41	0.46
Other industries (top 5 by skill bias)						
62 Computer Program	1.35	1.26	0.22	0.00	0.04	0.90
35-39 Utilities	1.79	0.77	0.42	0.23	0.20	0.32
41-43 Construction	9.09	2.86	0.41	1.42	0.43	0.27
61 Telecom	0.16	0.04	0.01	0.01	0.00	0.25
20 Chemical and Pharma	1.31	0.29	0.10	0.02	0.03	0.20

Notes: The table shows the Machine Suppliers row and the top 5 "Other industries" ranked on the Skill Bias column. Column (1): pre-spike share of external employment. Columns (2)-(5): contribution to the effect on employment of each skill group in year 4 (% of pre-spike total employment). Last column: normalized skill-bias contribution = (High STEM - Low Non-STEM) / pre-spike share.

◂ Return

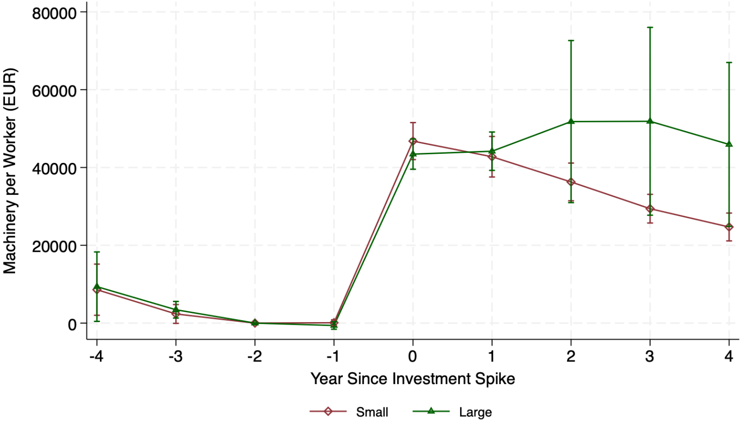
Machinery Stock per Worker around Spike



Notes: Machinery capital stock per worker around machinery investment spikes. Small firms have pre-spike employment below the median (13.1 FTE).

◂ Return ▸ Diff-in-diff

Machinery per Worker: Large versus Small Firms

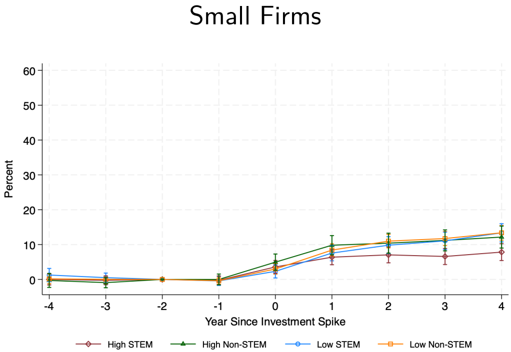


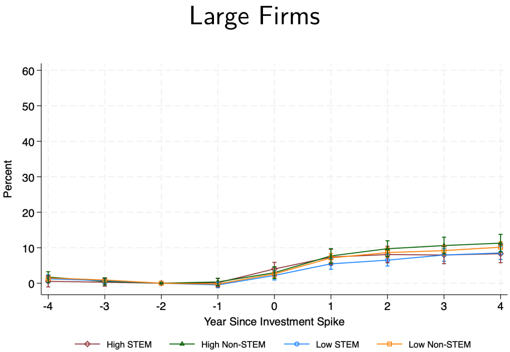
Notes: Difference-in-differences in machinery stock per worker, large versus small firms, around machinery investment spikes.

◂ Return

In-House Employment by Pre-Spike Firm Size

In-House Employment as a Share of Total Pre-spike Employment by Skill



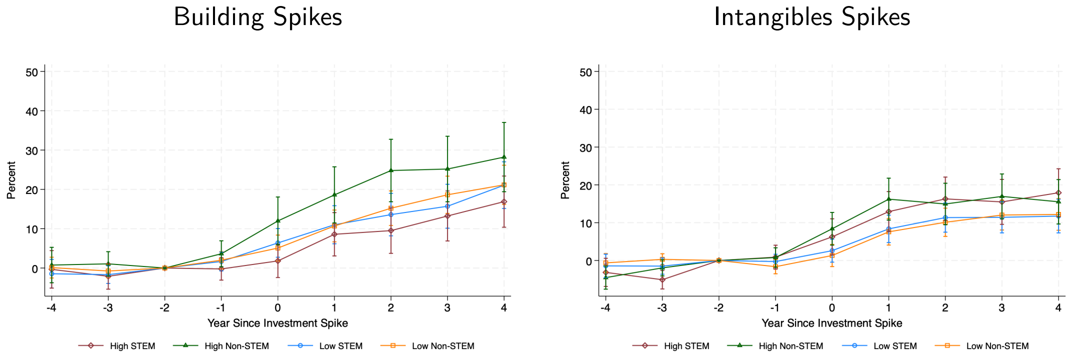


Notes: Smaller firms have total pre-spike employment below the median (13.1 FTE).

Return

In-House Employment by Capital Type

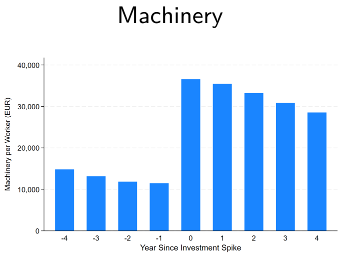
In-House Employment as a Share of Total Pre-spike Employment by Skill

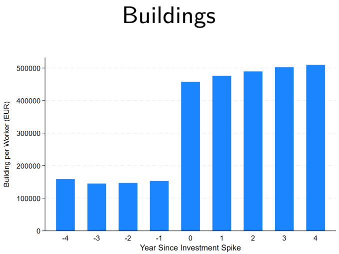


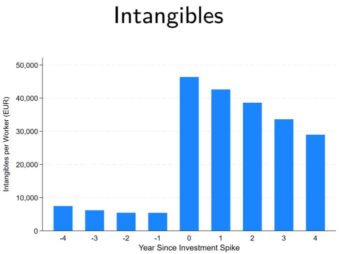
Notes: Diff-in-diff relative to industry average of non-spiking firms.

◂ Return

Capital Stock per Worker around Investment Spikes



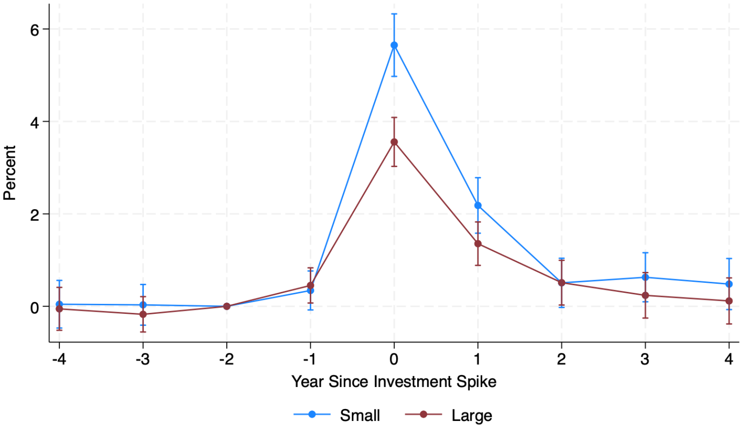




Notes: Capital stock per worker around investment spikes (85th-percentile cutoff) for machinery, buildings, and intangibles.

Return

Share of Machine Suppliers in Total Purchases



Notes: Share of machine suppliers in total purchases around machinery investment spikes, for small (Panel a) and large (Panel b) firms. Small firms have pre-spike employment below the median (13.1 FTE).

Return

Balance Table for Investment Spikes Strategy

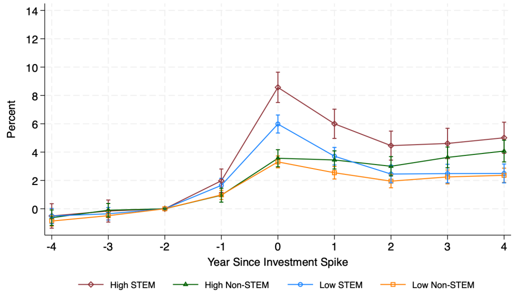
Table: Firm Employment before Machinery Investment Spikes

	Spiking		Non-Spiking		Std. Difference	
	In-House (1)	External (2)	In-House (3)	External (4)	In-House (5)	External (6)
Total employment	38.8	19.4	43.2	19.2	-0.01	0.00
	(324.0)	(131.9)	(82.3)	(60.9)		
Share of employment (%)						
— High STEM	4.9	5.8	6.0	6.1	-0.11	-0.05
	(10.4)	(5.8)	(6.6)	(3.4)		
— High non-STEM	13.9	16.4	15.1	16.2	-0.06	0.02
	(18.9)	(10.3)	(11.1)	(6.7)		
— Low STEM	26.1	24.8	24.4	23.6	0.08	0.11
	(22.4)	(10.6)	(11.3)	(6.1)		
— Low Non-STEM	55.1	53.0	54.6	54.2	0.02	-0.10
	(25.1)	(11.9)	(13.3)	(6.5)		
Observations	3,863		3,863			

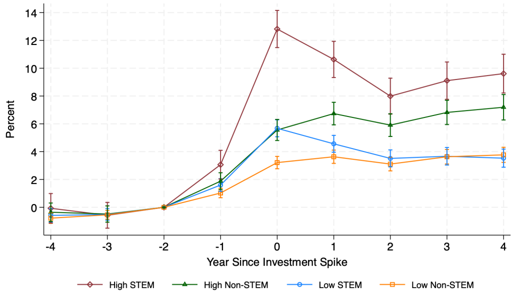
External Employment by Local Labor Markets: Other Industries

Employment as a Share of Total Pre-spike Employment by Skill

Other Industries: Inside LLM



Other Industries: Outside LLM



Notes: External employment from all other industries, split by whether the supplier is inside (Panel c) or outside (Panel d) the investing firm's local labor market.

Return

Levels of Education

Code	Description	Category	Share of Employment
0	Pre-primary education / less than primary education	Low	1.1%
02	Limited pre-primary education	Low	0.0%
10	Primary education	Low	5.9%
24	Lower secondary education – General	Low	9.0%
25	Lower secondary education – Vocational	Low	9.7%
34	Upper secondary education – General	Low	22.4%
35	Upper secondary education – Vocational	Low	13.3%
40	Post-secondary non-tertiary education	Low	2.6%
44	Post-secondary non-tertiary education – General	Low	0.4%
45	Post-secondary non-tertiary education – Vocational	Low	2.6%
55	Higher education – Short cycle – Vocational	High	0.2%
64	Higher education – Bachelor's or equivalent – Academic	High	0.1%
65	Higher education – Bachelor's or equivalent – Vocational	High	14.8%
74	Higher education – Master's or equivalent – Academic	High	9.1%
84	Doctorate or equivalent – Academic	High	0.3%
98	Highest degree not determined for persons younger than 15	Low	0.0%
99	Highest education level could not be determined	Low	5.1%
.	Missing	Low	3.3%

◂ Return

Fields of Education

Code	**Description**	Category	Share of Employment
00	Generic programmes and qualifications	Non-STEM	11.3%
01	Education	Non-STEM	1.0%
02	Arts and humanities	Non-STEM	3.9%
03	Social sciences, journalism and information	Non-STEM	2.1%
04	Business, administration and law	Non-STEM	11.3%
05	Natural sciences, mathematics and statistics	STEM	1.6%
06	Information and Communication Technologies	STEM	1.6%
07	Engineering, manufacturing and construction	STEM	26.7%
08	Agriculture, forestry, fisheries and veterinary	Non-STEM	1.1%
09	Health and welfare	Non-STEM	2.3%
10	Services	Non-STEM	3.6%
99	Not specified	Non-STEM	30.2%
NA	Not available	Non-STEM	0.0%

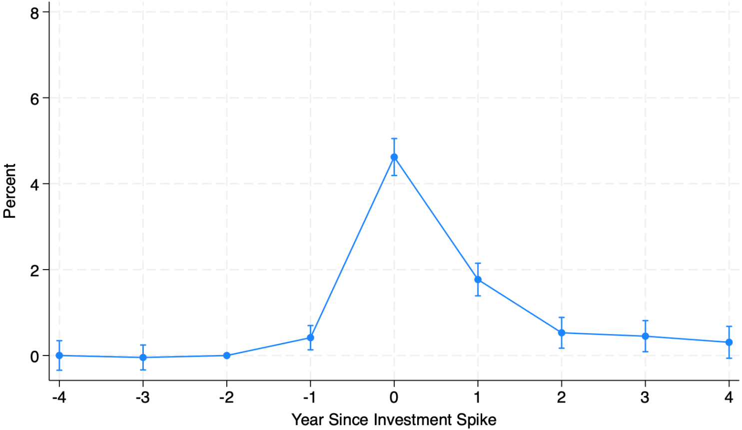
◂ Return

Machine Supplier Industries

Type	NACE
Builders	2562, 28
Installers	33, 4321
Distributors	4614, 466
Advisors	71, 7022

◂ Data & Measurement ◂ Suppliers First

B2B Transactions: Purchases from Machine Supplier Industries



Notes: Share of purchases from machine suppliers around machinery investment spikes, all private-sector firms.

◂ Return ▸ External List Validation ▸ Robot Imports Validation

A Robot-Integration Project in the Transaction Data

A typical project (sources: HowToRobot, IFR, RIA, CSIA, Orgalime)

- Robot cell $\approx$ €250k: $\sim$1/3 robot hardware, $\sim$2/3 integration services
  (engineering & cell design, safety guarding, programming, installation, commissioning, training)
- Performed by the integrator's high-STEM engineers — not the manufacturer's staff

Spike year: the project

- Milestone billing (Orgalime S 2012): 1/3 at order, 1/3 ready for delivery, 1/3 at delivery
- Project spans a few months $\rightarrow$ full €250k recorded as B2B purchases in the spike year

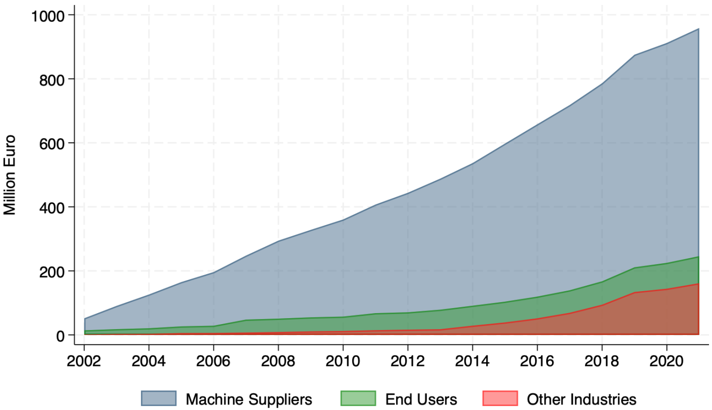
After commissioning: servicing

- Maintenance, spare parts, support, reprogramming: $\sim$10–12% of system cost per year

Explains the time profile of external high-STEM demand:
spike-year burst, then persistent elevated level

Return

Accumulated Robot Imports by Sector of Importing Firm

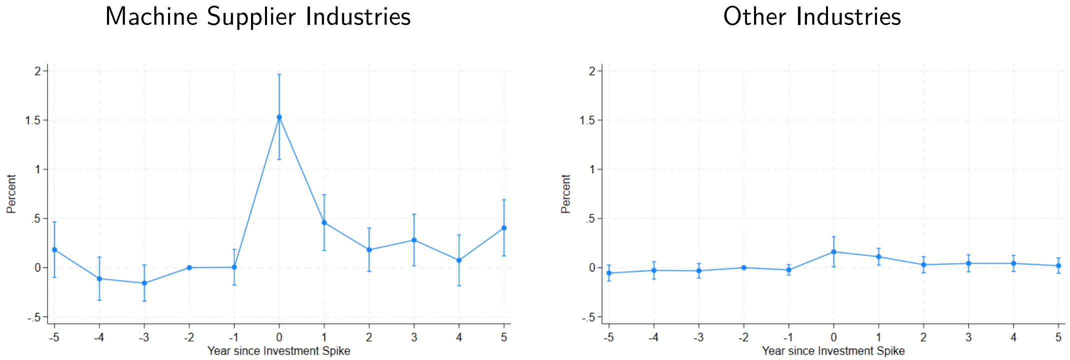


Notes: Accumulated aggregate imports of industrial robots (HS code 847950) to Belgium, split by the industry of the importer.

◂ Return

External List Validation

Share of Purchases from External List of Robot Supplier Firms



Notes: Purchases of spiking firms from an external list of robot suppliers, split by whether the suppliers are in our machine supplier industry codes (Panel a) or other industries (Panel b).

◂ Return

Balance Table: Small Firms

Table: Small Firms: Firm Employment before Machinery Investment Spikes

	Spiking		Non-Spiking		Std. Difference	
	In-House (1)	External (2)	In-House (3)	External (4)	In-House (5)	External (6)
Total employment	5.7	2.2	6.2	1.9	-0.09	-0.01
	(5.2)	(2.2)	(.7)	(.6)		
Share of employment (%)						
— High STEM	3.3	5.3	3.5	4.9	-0.02	0.08
	(10.2)	(5.8)	(5.5)	(3.0)		
— High non-STEM	13.4	17.0	13.8	16.3	-0.02	0.06
	(21.3)	(11.3)	(12.0)	(6.5)		
— Low STEM	26.2	25.2	23.8	24.5	0.10	0.07
	(26.1)	(11.5)	(12.8)	(6.3)		
— Low Non-STEM	57.1	52.5	59.0	55.4	-0.07	-0.16
	(28.3)	(12.5)	(12.9)	(6.1)		
Observations	1,926		1,926			

◂ Return

Balance Table: Large Firms

Table: Large Firms: Firm Employment before Machinery Investment Spikes

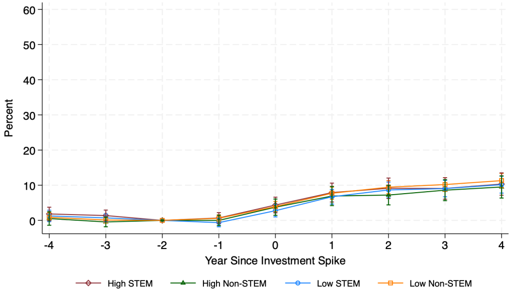
	Spiking		Non-Spiking		Std. Difference	
	In-House (1)	External (2)	In-House (3)	External (4)	In-House (5)	External (6)
Total employment	71.8	36.5	76.7	35.2	-0.01	0.01
	(455.8)	(183.6)	(117.7)	(87.5)		
Share of employment (%)						
— High STEM	6.5	6.3	6.9	6.5	-0.04	-0.04
	(10.5)	(5.7)	(6.9)	(3.7)		
— High non-STEM	14.4	15.7	15.3	16.0	-0.05	-0.03
	(16.2)	(9.3)	(10.4)	(6.3)		
— Low STEM	25.9	24.4	25.0	23.6	0.05	0.09
	(18.1)	(9.5)	(10.7)	(5.7)		
— Low Non-STEM	57.1	53.5	59.0	53.9	-0.07	-0.03
	(28.3)	(11.4)	(12.9)	(6.5)		
Observations	1,926		1,926			

◂ Return

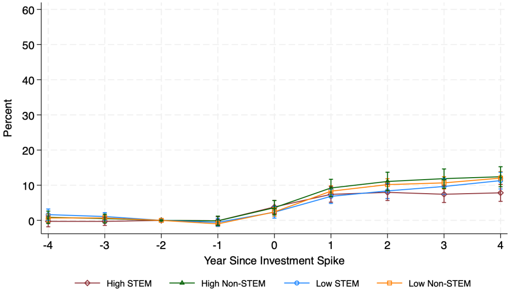
Sector Heterogeneity: In-House Employment

In-House Employment as a Share of Total Pre-spike Employment by Skill

Manufacturing

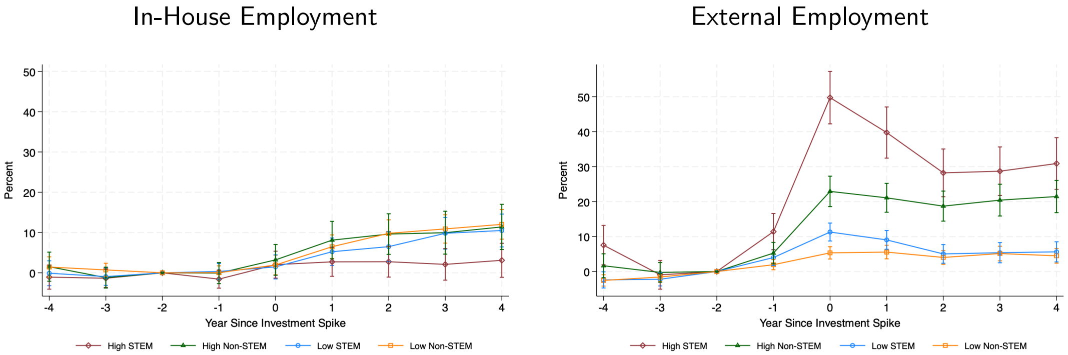


Services



◂ Return ▸ Balance: Manuf. ▸ Balance: Services

Employment around Investment Spikes: Agriculture/Utilities/Construction



Notes: Private-sector firms in agriculture, utilities, and construction around first machinery investment spike.

◂ Return

Balance Table: Manufacturing

Table: Manufacturing: Firm Employment before Machinery Investment Spikes

	Spiking		Non-Spiking		Std. Difference	
	In-House (1)	External (2)	In-House (3)	External (4)	In-House (5)	External (6)
Total employment	63.5	27.3	69.5	28.2	-0.03	-0.01
	(215.6)	(95.8)	(117.4)	(77.7)		
Share of employment (%)						
— High STEM	6.1	6.5	7.2	6.8	-0.11	-0.05
	(9.5)	(5.5)	(5.2)	(2.6)		
— High non-STEM	10.6	14.9	11.4	14.0	-0.06	0.11
	(13.3)	(8.1)	(6.2)	(6.7)		
— Low STEM	32.8	26.3	32.3	25.7	0.03	0.06
	(21.0)	(9.2)	(8.7)	(4.5)		
— Low Non-STEM	50.4	52.3	49.2	53.5	0.05	-0.11
	(22.1)	(10.7)	(9.6)	(5.1)		
Observations	1,226		1,226			

◂ Return

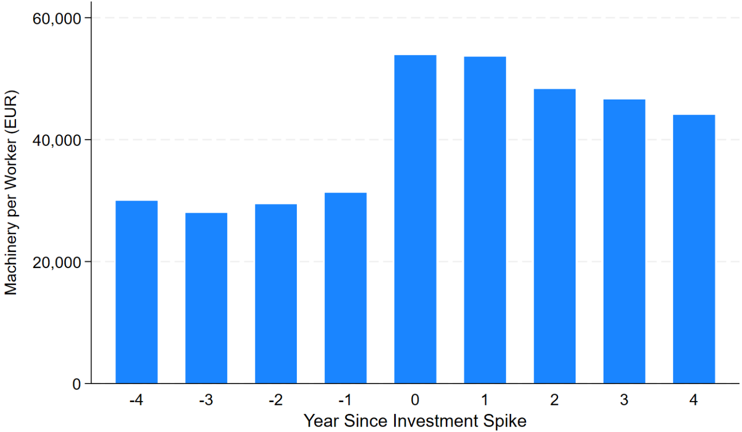
Balance Table: Services

Table: Services: Firm Employment before Machinery Investment Spikes

	Spiking		Non-Spiking		Std. Difference	
	In-House (1)	External (2)	In-House (3)	External (4)	In-House (5)	External (6)
Total employment	26.1	13.6	30.8	14.0	-0.01	-0.00
	(388.6)	(82.2)	(34.8)	(20.4)		
Share of employment (%)						
— High STEM	4.3	5.6	5.5	5.9	-0.11	-0.05
	(10.9)	(6.3)	(7.8)	(4.1)		
— High non-STEM	18.1	18.4	19.7	19.2	-0.07	-0.07
	(21.9)	(11.6)	(12.5)	(7.3)		
— Low STEM	19.7	22.1	17.8	20.7	0.09	0.13
	(19.6)	(10.4)	(8.4)	(5.1)		
— Low Non-STEM	57.9	53.9	56.9	54.1	0.04	-0.02
	(25.5)	(12.7)	(14.7)	(7.2)		
Observations	2,011		2,011			

◂ Return

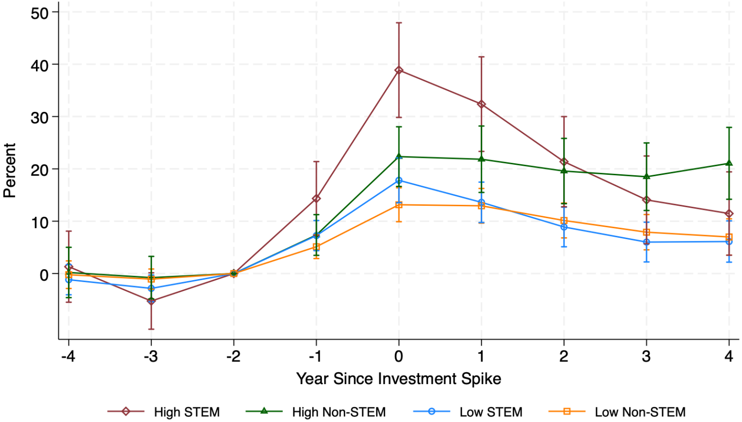
Machinery around Building Investment Spikes



Notes: Machinery capital stock per worker around building investment spikes (90th-percentile cutoff, €220,195).

Return

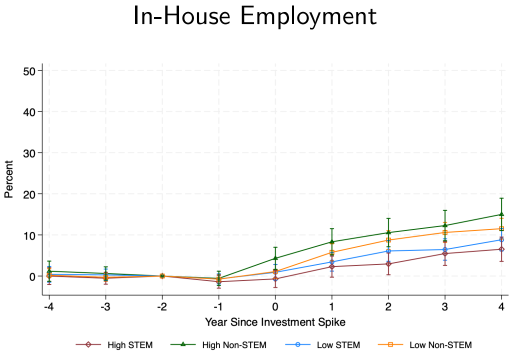
Building Spikes: Excluding Machine Spikes

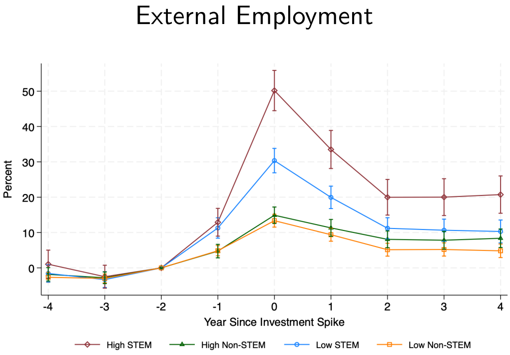


Notes: External employment around building investment spikes, excluding spikes with machinery-stock-per-worker growth above the 25th percentile.

◂ Return

Building Spikes: Cutoff 85th Percentile





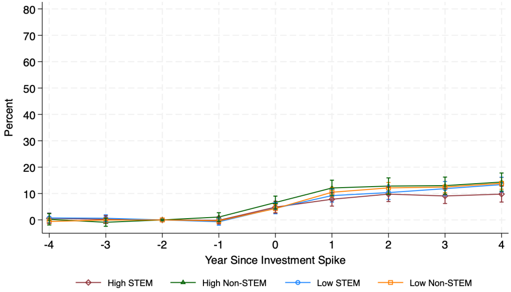
Notes: Private-sector firms around building investment spikes defined at the 85th-percentile cutoff (€137k).

◂ Return

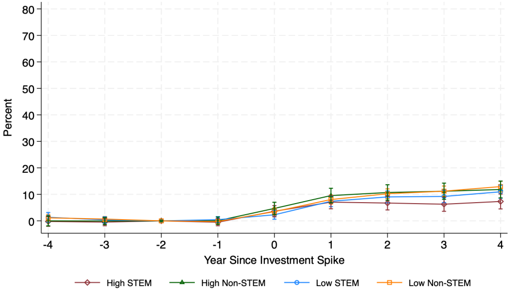
In-House Employment around Machinery Spikes: New vs. Existing Supply

In-House Employment as a Share of Total Pre-spike Employment by Skill

Spikes Driven by New Suppliers



Spikes Driven by Existing Suppliers



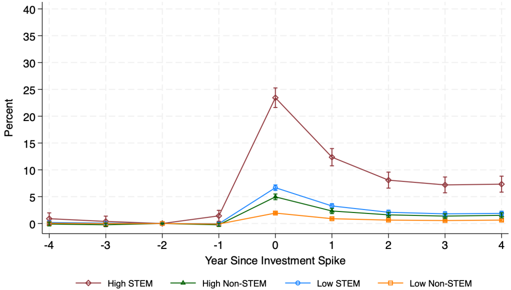
Notes: Diff-in-diff relative to industry average of non-spiking firms.

◂ Return ▸ Machine Suppliers ▸ Other Industries

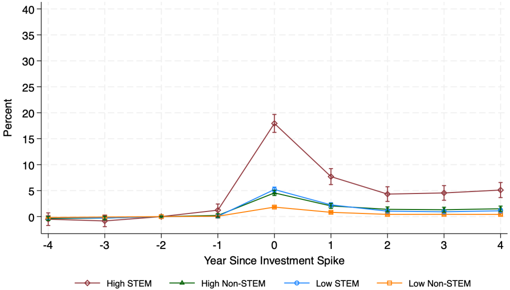
External Employment around Machinery Spikes: Machine Suppliers

Employment as a Share of Total Pre-spike Employment by Skill

Spikes Driven by New Suppliers



Spikes Driven by Existing Suppliers



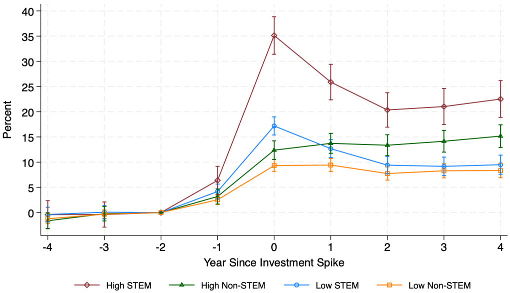
Notes: External employment from machine suppliers only.

◂ Return

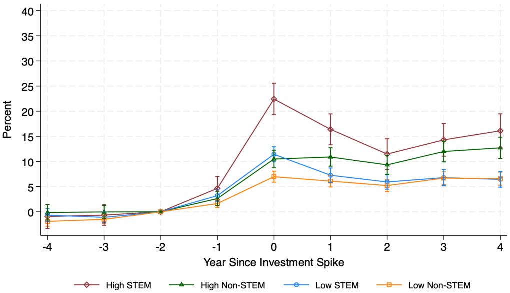
External Employment around Machinery Spikes: Other Industries

Employment as a Share of Total Pre-spike Employment by Skill

Spikes Driven by New Suppliers



Spikes Driven by Existing Suppliers



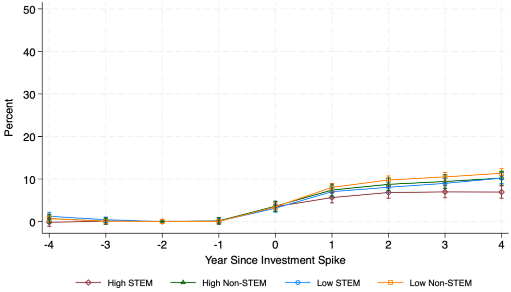
Notes: External employment from all other (non-machine-supplier) industries.

Return

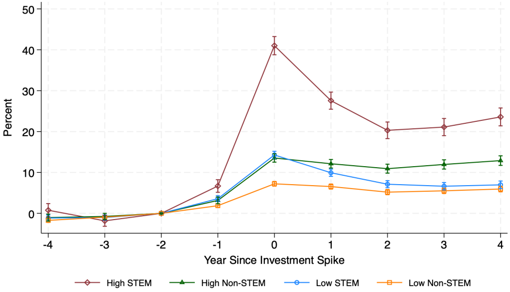
Employment around Machinery Spikes: Cutoff 85th Percentile

Employment as a Share of Total Pre-spike Employment by Skill

In-House Employment



External Employment



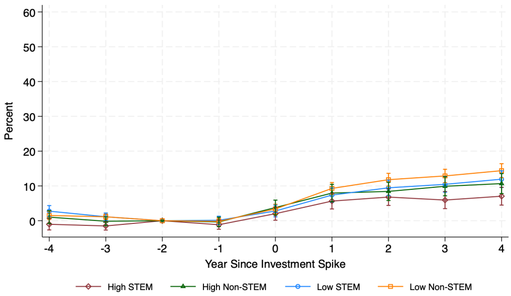
Notes: Machinery investment spikes defined at the 85th-percentile cutoff.

◂ Return ▸ 95th Percentile Cutoff

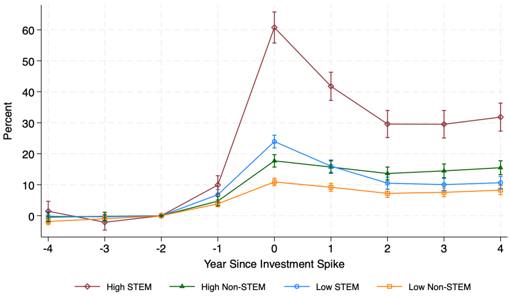
Employment around Machinery Spikes: Cutoff 95th Percentile

Employment as a Share of Total Pre-spike Employment by Skill

In-House Employment



External Employment



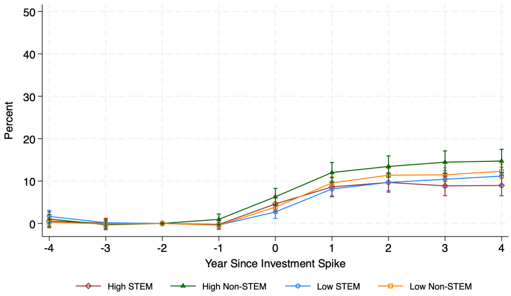
Notes: Machinery investment spikes defined at the 95th-percentile cutoff.

◂ Return

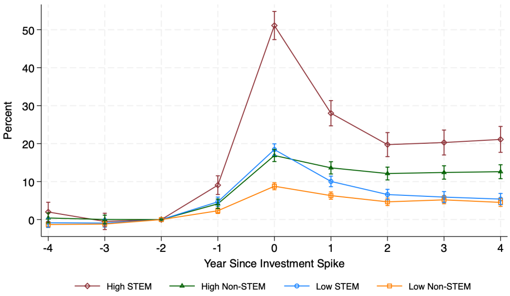
Single-Spiking Firms: Employment around Machinery Spikes

Employment as a Share of Total Pre-spike Employment by Skill

In-House Employment



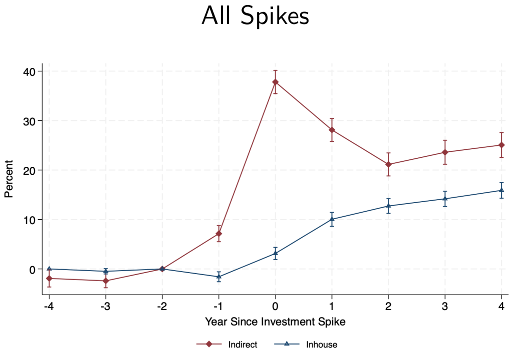
External Employment

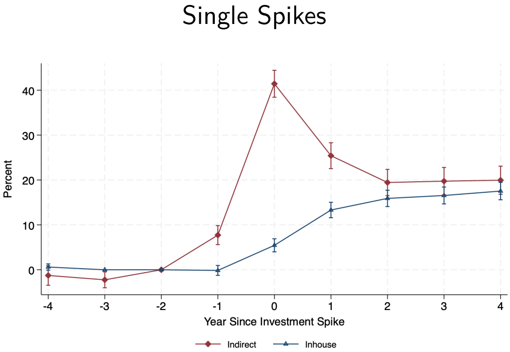


Notes: Sample limited to the 61% of firms with a single machinery investment spike.

◂ Return ▸ External vs. In-House

External and In-House Employment around Machinery Spikes

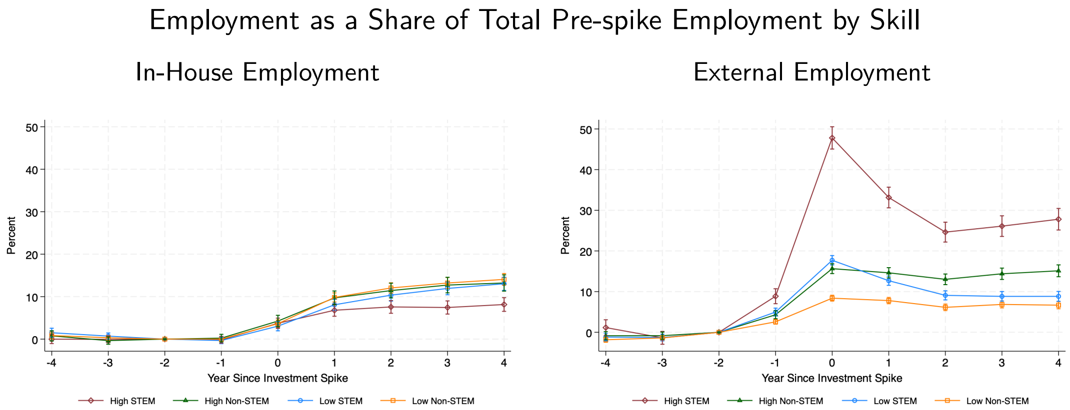




Notes: In-house employment (% of pre-spike in-house) and external employment (% of pre-spike external).
Panel (a) all spikes; Panel (b) single-spiking firms only.

Return

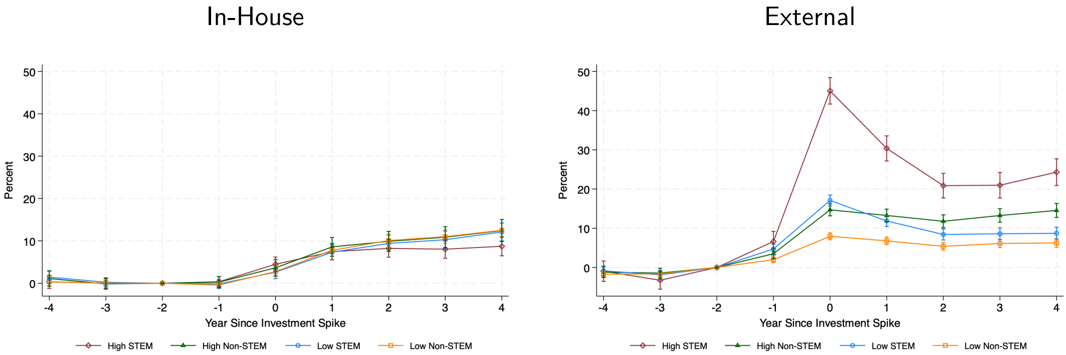
Including Exiting Firms: Employment around Machinery Spikes



Notes: Firm exits assigned zero in-house and external employment.

Employment around Machinery Spikes: Random One-to-one Matching

Employment as a Share of Total Pre-spike Employment by Skill



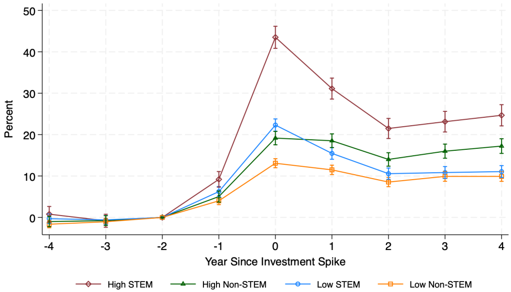
Notes: Control group selected via random one-to-one matching within industry-year cells.

◂ Return

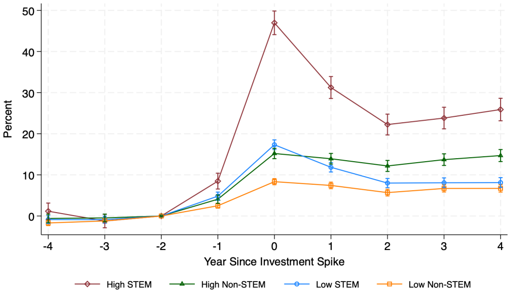
Higher-Order Supplier Links: External Employment

Employment as a Share of Total Pre-spike Employment by Skill

3rd-Order (Figure E.7.a)



1st-Order (Figure 2.b)



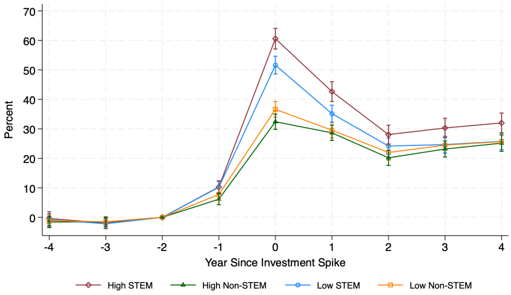
Notes: External employment in % of pre-spike *total* employment. Left: higher-order (3rd-order) supplier links; Right: first-order only (baseline).

Return Drivers

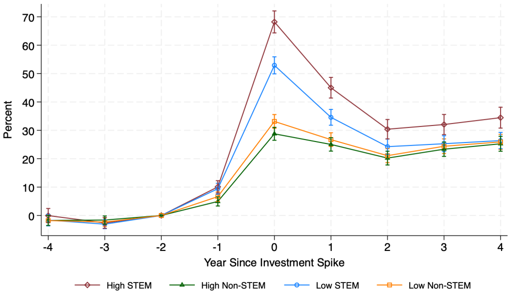
Higher-Order Supplier Links: Drivers of External Skill Bias

Employment as a Share of Pre-spike *External* Employment by Skill

3rd-Order (Figure E.7.b)



1st-Order (Figure C.1.b)



Notes: External employment in % of pre-spike *external* employment. Left: higher-order (3rd-order) supplier links; Right: first-order only.

◂ Return

Aggregate Implications: Framework

Integration vs. production labor

- Temporary employment response around year of spike → *integration* (installing new I)
- Stable effect 4 years post-spike → *production* (running expanded stock K)

Step 1: Partial-equilibrium shift (Autor et al., 2013; Mian and Sufi, 2014)

- Move economy from $M_0 \to M_1$; require investment $\Delta I = \delta \cdot \Delta M$
- β_M: DiD on machinery/worker; β^u_{ms}: DiD on employment of skill s in stage u via mode m

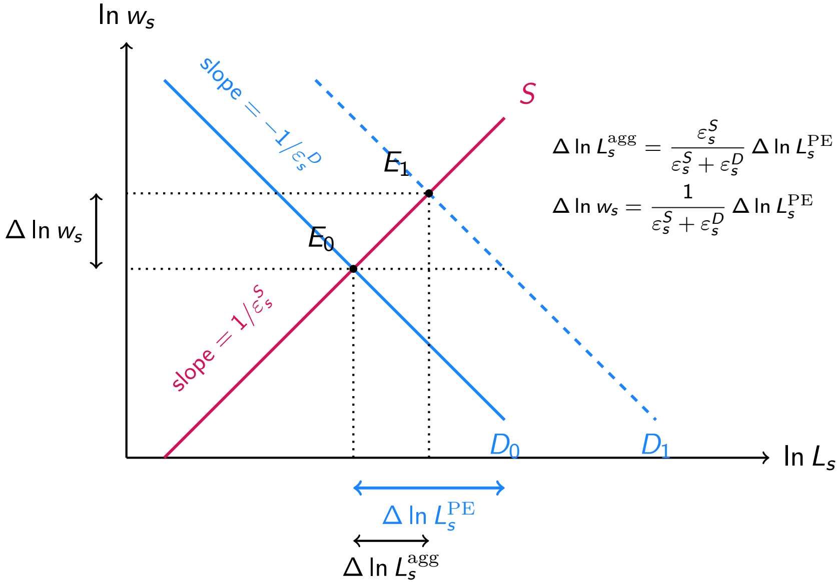
$$\mathcal{B}^P_{ms} = \beta^P_{ms} \times \frac{\Delta M}{\beta_M}, \qquad \mathcal{B}^I_{ms} = \beta^I_{ms} \times \delta \times \frac{\Delta M}{\beta_M}.$$

Step 2: General-equilibrium adjustment (Krusell et al., 2000; Moll, 2021)

$$\Delta \ln L_s = \frac{\varepsilon^S_s}{\varepsilon^S_s + \varepsilon^D_s} \Delta \ln L^{PE}_s, \qquad \Delta \ln w_s = \frac{1}{\varepsilon^S_s + \varepsilon^D_s} \Delta \ln L^{PE}_s.$$

◂ Return ▸ GE Adjustment ▸ Parameters

General-Equilibrium Adjustment in the Skill Labor Market



$$\Delta \ln L_s^{\mathrm{agg}} = \frac{\varepsilon_s^S}{\varepsilon_s^S + \varepsilon_s^D} \Delta \ln L_s^{\mathrm{PE}}$$

$$\Delta \ln w_s = \frac{1}{\varepsilon_s^S + \varepsilon_s^D} \Delta \ln L_s^{\mathrm{PE}}$$

Aggregate Implications: Parameter Values

1. Aggregate ΔM (machinery per worker, 2003–2021): from time series
2. $\beta_M =$ €45,000: year-0 DiD on machinery per worker (€45,100 pooled across spiking firms)
3. β^u_{ms}: DiD employment effects from Figure 2 (empl. by skill and mode)
   - Integration: sum of year 0–2 effects
   - Production: year-4 effect
4. Depreciation rate $\delta = 12\%$ (BEA machinery rate) (Fraumeni, 1997)
5. GE elasticities: central calibration $\varepsilon^S_s = \varepsilon^D_s = 1.5$ (Katz and Murphy, 1992; Krusell et al., 2000; Goldin and Katz, 2008)

Aggregate Machinery per Worker

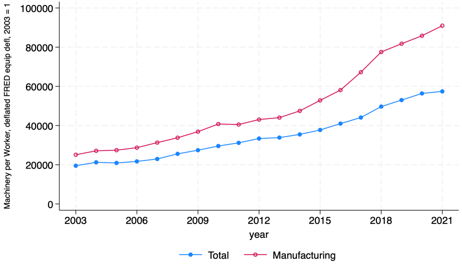


Table reports $\mathcal{B}^u_{m,s} - \mathcal{B}^u_{m,\mathrm{LowNon}}$ (differences vs. Low Non-STEM).

◂ Return ▸ GE Sensitivity

GE-Adjusted Aggregate Skill Bias: Sensitivity to Supply Elasticity

ε_s^S	Employment Bias (pp)	Skill Premium (pp)
∞ (Autor et al.; Mian-Sufi)	20.5	0.0
4.50	15.3	3.4
1.50 (central)	**10.2**	**6.8**
0.50	5.1	10.2
0 (Krusell et al.)	0.0	13.6

Notes: GE-adjusted high-STEM skill bias (vs. low non-STEM) across skill-supply elasticities ε_s^S, holding $\varepsilon_s^D = 1.5$, applied to the 20.5pp PE total. $\varepsilon_s^S \to \infty$ recovers Autor et al. (2013) and Mian and Sufi (2014); $\varepsilon_s^S = 0$ recovers Krusell et al. (2000).

◂ Return ▸ Parameters

Robustness & Alternative Approaches

Results robust to ...

- Spike events: Focusing on single-spiking firms ‣ Link ; varying spike threshold ‣ Link
- Unbalanced sample: Including exits as zero employment ‣ Link
- Control group: Using random one-to-one matching ‣ Link ; using later-spiking or never-spiking ("clean") controls
- External employment: Including higher-order links (suppliers of suppliers...) ‣ Link
- Application sector: Skill bias of new machinery is pervasive ‣ Link

Firm-to-firm linkages are key for capturing the external skill bias ...

- Local labor markets: capital-complementary skills often sourced outside CZs ‣ Link
  (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Aghion et al., 2023)
- Sectoral input-output: investing firms shift toward high-STEM suppliers ‣ Link
  (Humlum, 2022; ...)

◂ Main Results ◂ Estimation

Analysis Sample

Sample restrictions

1. Focus on first spike event (65% of spiking firms single-spike)
2. At least 5 employees before the spike
3. Balanced sample 4 years before/after the spike

Control group: non-spiking firms in same NACE-3 industry $\times$ event year, satisfying the sample criteria but not spiking in the event year.

Estimator: stacked difference-in-differences (Callaway and Sant'Anna, 2021)

New vs. Existing Suppliers: Classification

Definition. For each machinery spike, let Δ_{new} be the change in purchases from *new* machine suppliers (firms that had not sold to the investing firm before), and Δ_{exist} be the change from *existing* machine suppliers. Define the new-supplier share of the spike:

$$S_{\text{new}} = \frac{\Delta_{\text{new}}}{|\Delta_{\text{new}}| + |\Delta_{\text{exist}}|}$$

Classification.

- Drop spikes with *negative* total change in purchases from machine suppliers.
- *New-supplier spike*: S_{new} above sample median.
- *Existing-supplier spike*: S_{new} at or below sample median.

Splits spiking firms into roughly equal-sized groups defined by whether the spike is driven by new vs. existing supplier relationships.

Return

Specification & Outcome Variables

Difference-in-differences around spike year e, relative to $k = -2$:

$$Y_{sjt} = \beta_1 \text{Spike}_{je} + \sum_{k} \beta_{0k} \mathbf{1}_{\{t=e+k\}} + \sum_{k \neq -2} \beta_{1k} \, \text{Spike}_{je} \, \mathbf{1}_{\{t=e+k\}} + \varepsilon_{sjt}$$

- $\text{Spike}_{je} = 1$ if firm j spikes in year e; event-time indicators $\mathbf{1}_{\{t=e+k\}}$
- Coefficients of interest: β_{1k}, $k \neq -2$ (parallel trends assumption), estimated separately by skill s

Outcomes Y_{sjt}: employment of skill group s $\times$ mode m (in-house / external) $\times$ supplier type (machine supplier / other)

- Normalized by total pre-spike employment in skill group s (avg. of $k \in \{-3, -2, -1\}$)
- Common denominator avoids zero-denominator issues in disaggregated groups (Chen and Roth, 2024)

Control group: non-spiking firms in same NACE-3 industry $\times$ event year, satisfying the sample criteria (pre-spike employment, no previous spikes, balanced panel)

Standard errors: clustered at the event (treated–control pair) level

Sample Reduction Table

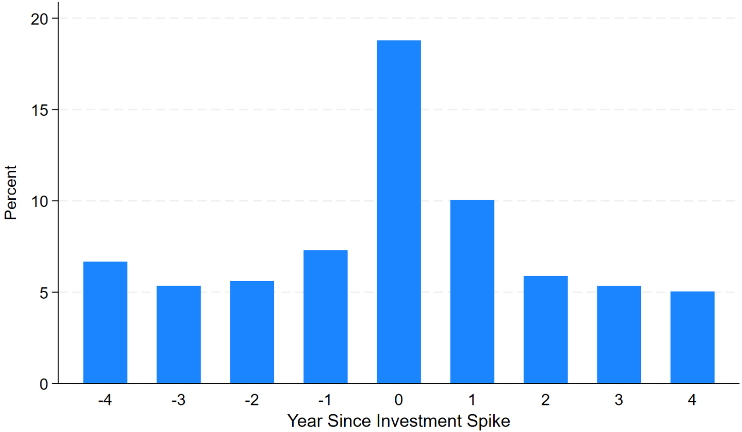
Table: Machinery Investment Spikes Sample Reduction

Sample Step	Firms (1)	Investment Spikes (2)
1. Private sector firms with machinery spike	37,379	57,783
2. Pre-spike employment	9,463	15,542
3. First investment spike	9,463	9,463
4. Balanced sample	3,863	3,863

Notes: This table shows how our analysis sample shrinks with the sample criteria listed in Section **??**. Column (1) shows the number of eligible firms, and Column (2) shows their number of machinery investment spikes.

◂ Return

Investment as a Share of Sales around Machinery Spikes



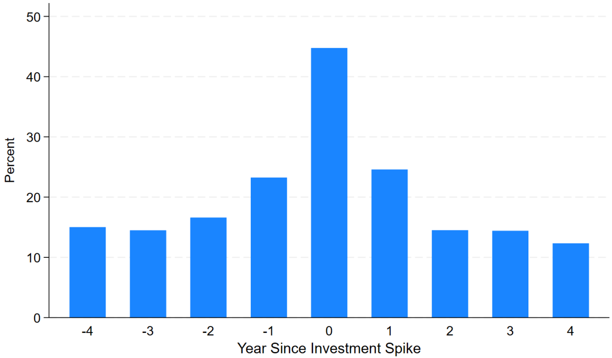
Notes: Total fixed investment as a share of sales (VAT records; not split by asset type). Investment peaks at ∼20% of sales in the spike year and returns to baseline: the investment *flow* is a one-off event even as the machinery *stock* remains elevated.

Return

Building Investment Spikes Definition

$$\text{Spike}_{jt} = \mathbf{1}[i_{jt} \geq i_{P85|+}] \quad \text{with} \quad i_{jt} = \frac{\Delta \text{Buildings}_{jt}}{\frac{1}{2}(L_{jt} + L_{jt-1})}, \quad i_{P85|+} = €137{,}000$$

Investment as a Share of Sales around Spike

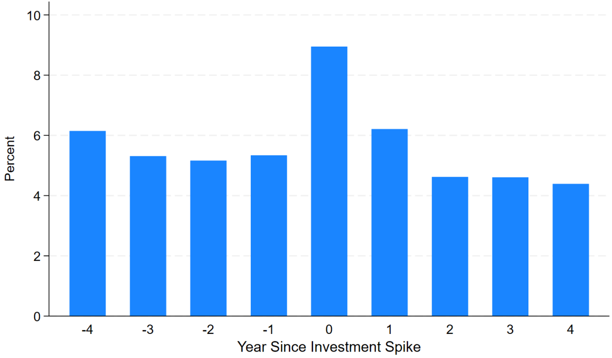


Return

Intangibles Spikes Definition

$$\text{Spike}_{jt} = \mathbf{1}[i_{jt} \geq i_{P85|+}] \quad \text{with} \quad i_{jt} = \frac{\Delta \text{Intangibles}_{jt}}{\frac{1}{2}(L_{jt} + L_{jt-1})}, \quad i_{P85|+} = \text{€}\,14{,}000$$

Investment as a Share of Sales around Spike



◂ Return

Skill-Mix Stability across Customer Mixes (Machine Suppliers)

Specification. Regress a machine supplier's employment share of each skill group on the share of its revenue from spiking-firm clients, with supplier and year fixed effects

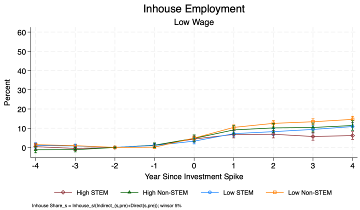
	High STEM (1)	High Non-STEM (2)	Low STEM (3)	Low Non-STEM (4)
Spiking-Client Revenue Share (%)	.0018	−.0012	−.0012	.0006
	(.0042)	(.0067)	(.0048)	(.0063)
Mean of dep. var. (%)	13.3	22.8	23.0	40.9
Supplier FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	257,332			

Notes: Estimated coefficients are economically and statistically close to zero: a machine supplier's skill composition does *not* track its customer mix $\Rightarrow$ structurally specialized workforce. Machine suppliers derive 1.76% of revenue from spiking-firm clients, vs. 0.69% at non-machine suppliers. SEs clustered by supplier. *Sample*: Belgian machine suppliers, 2003–2021.

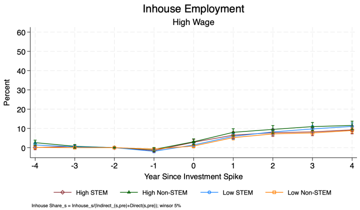
Wage-Savings Motive: Low-Wage Firms Outsource *More*

Employment as a Share of Total Pre-spike Employment by Skill

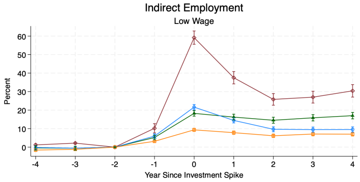
In-House: Low-Wage Firms



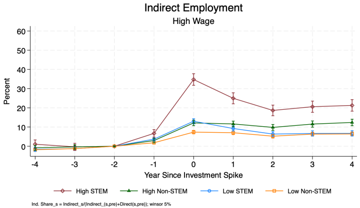
In-House: High-Wage Firms



External: Low-Wage Firms



External: High-Wage Firms



◂ Additional Evidence ◂ Supply Side ▸ Wage Premia

Wage Premia of Machine Suppliers vs. Investing Firms

	Dependent variable: log average wage	
	(1)	(2)
Machine supplier	.138***	.036***
	(.008)	(.007)
Year fixed effects	✓	✓
Skill share controls		✓
Observations	86,196	86,196

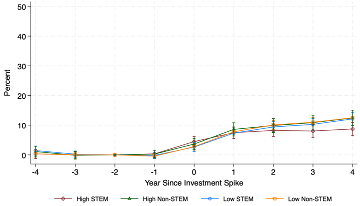
Notes: Machine suppliers and spiking firms in the pre-spike year (>5 employees); firm-clustered SEs. Adding skill-share controls (Col. 2) → a **3.6%** premium for a comparable workforce. *** $p < 0.01$.

◂ Return

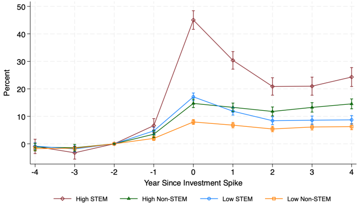
Robust to Controlling for Sales Growth

Employment as a Share of Total Pre-spike Employment by Skill

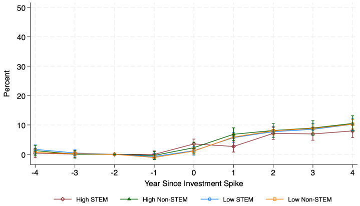
In-House: Baseline



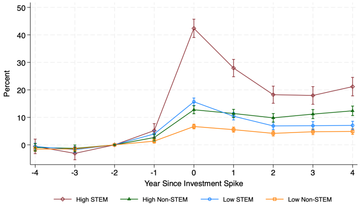
External: Baseline



In-House: Controlling for Sales Growth



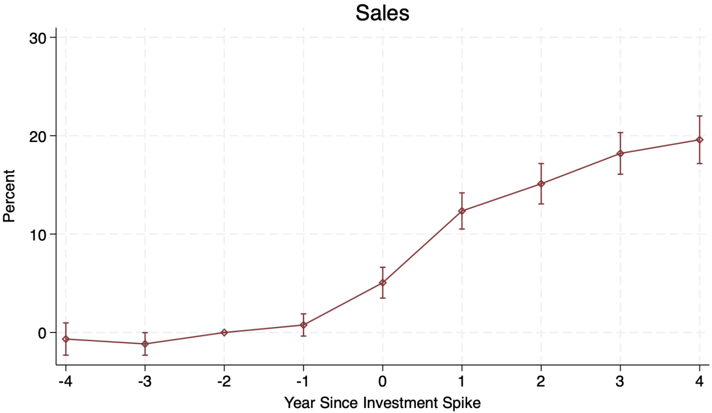
External: Controlling for Sales Growth



◂ Main Results ◂ Identification ▸ Sales around Spikes

Notes: Controlling flexibly for year $-2 \to 0$ sales growth leaves the external high-STEM skill bias essentially

Sales around Machinery Investment Spikes



Notes: Log sales (%) around spikes, diff-in-diff vs. non-spiking firms (same design as Figure 2). Sales rise smoothly to ∼20% by year 4, with no pre-trend.

◂ Return

Model Predictions

Prediction 1. Capital investment raises the relative demand for skills through two channels:

1(a) *Capital-skill complementarity* (Griliches, 1969; Krusell et al., 2000): capital stock K raises demand for skilled *production* labor S^P

1(b) *Investment-skill complementarity* (Goldin and Katz, 1998): investment I raises demand for skilled *integration* labor S^I

↔ Main result

Prediction 2 (Fixed costs → outsourcing). Fixed costs of in-house hires (e.g., indivisibilities) ⇒ skills sourced externally, more so by *smaller firms*. ↔ Firm Size

Prediction 3 (Lumpy investments → outsourcing). Hiring/firing costs make outsourcing more prevalent for *lumpy* capital (buildings/machinery vs. intangibles). ↔ Capital Types

Prediction 4 (Advanced capital → outsourcing). If skill bias is embodied, stronger effects for *rapidly-changing* capital (machinery vs. buildings; new vs. existing suppliers).

↔ Capital Types & New-vs-Existing

◂ Return

Substitution Elasticities: Derivation & Calibration

Nested CES

$$H = \left[\alpha K^{\rho} + (1-\alpha)L_S^{\rho}\right]^{1/\rho}, \ \ \sigma_{KS} = \tfrac{1}{1-\rho}; \qquad Y = [(1-\mu)H^{\eta} + \mu L_U^{\eta}]^{1/\eta}, \ \ \sigma_{HU} = \tfrac{1}{1-\eta}$$

Derivation: spike = firm-specific user-cost decline (wages fixed); log-differentiate the cost-minimizing factor demands; the latent shock cancels:

$$\frac{\sigma_{HU}}{\sigma_{KS}} = 1 + \frac{1}{s_K^H} \cdot \frac{\Delta \ln L_S - \Delta \ln L_U}{\Delta \ln K - \Delta \ln L_S} \approx 1 + 3 \cdot \frac{0.29 - 0.17}{0.9 - 0.29} \approx 1.6$$

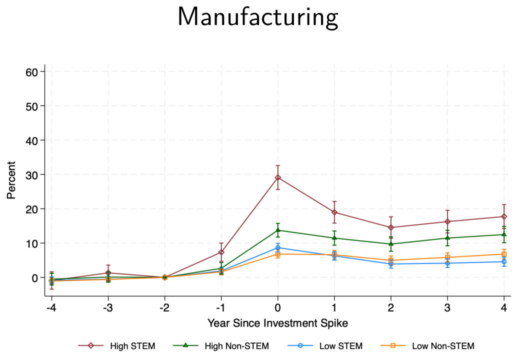
Calibration (stable year-4 responses $\to$ production margin)

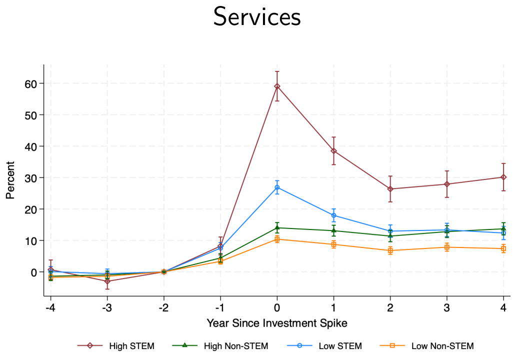
- High-STEM +34% ($\Delta \ln L_S = 0.29$); low non-STEM +18% ($\Delta \ln L_U = 0.17$)
- Machinery deepening $\Delta \ln K \approx 0.9$ (€16k $\to$ €40k per worker)
- Machinery cost share in inner nest $s_K^H = rK/(rK + w_S L_S) \approx 1/3$
  (user cost $r \approx 0.17$; pre-spike machinery $\approx$ €16k/worker; baseline $L_S \approx 3.0$ FTE at $w_S \approx$ €75k, Eurostat)
- Requires only no factor-*biased* shock at the spike (neutral/scale shocks cancel)
- Krusell et al. (2000), aggregate: $\sigma_{KS} = 0.67$, $\sigma_{HU} = 1.67 \Rightarrow$ ratio ≈ 2.5

Return

Skill Bias of New Machinery Is Pervasive across Sectors

External Employment as a Share of Total Pre-spike Employment by Skill





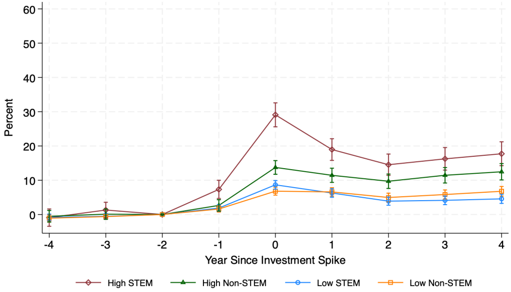
Notes: Manufacturing vs. services firms around first machinery investment spike.

◂ Return ▸ In-House Employment ▸ Agri/Util/Constr ▸ Balance: Manuf. ▸ Balance: Services

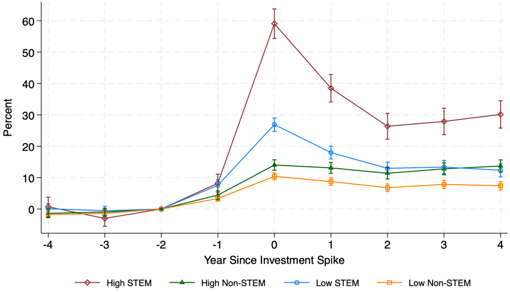
Skill Bias of New Machinery Is Pervasive across Sectors

External Employment as a Share of Total Pre-spike Employment by Skill

Manufacturing



Services

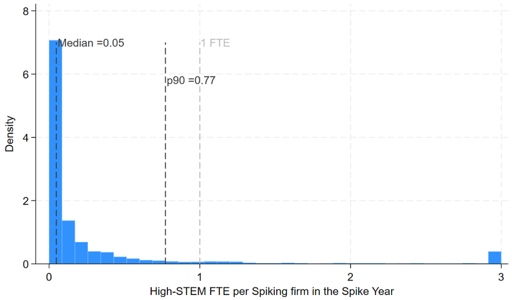


Consistent with scale economies in machine-complementary skills
(services less machine intensive)

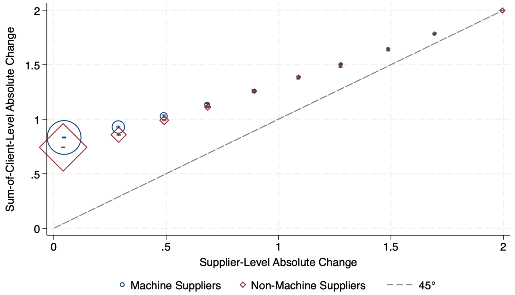
◂ Return ▸ In-House Employment ▸ Agri/Util/Constr ▸ Balance: Manuf. ▸ Balance: Services

Specialized Suppliers Pool Indivisible, Lumpy Demand across Clients

External High-STEM Labor per Spiking Firm



Workforce Smoothing at Machine Suppliers

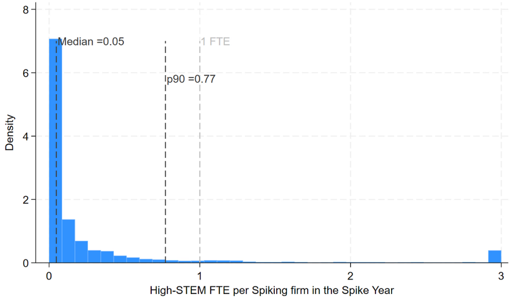


Notes: Left: high-STEM FTE each spiking firm sources from a machine supplier (median 0.05 FTE). Right: machine suppliers smooth their workforce across many clients.

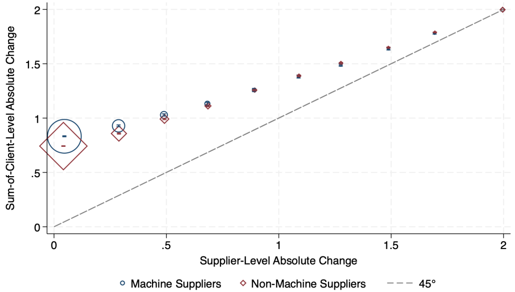
◂ Return ▸ Skill-Mix Stability ▸ Wage-Savings Motive

Specialized Suppliers Pool Indivisible, Lumpy Demand across Clients

External High-STEM Labor per Spiking Firm



Workforce Smoothing at Machine Suppliers

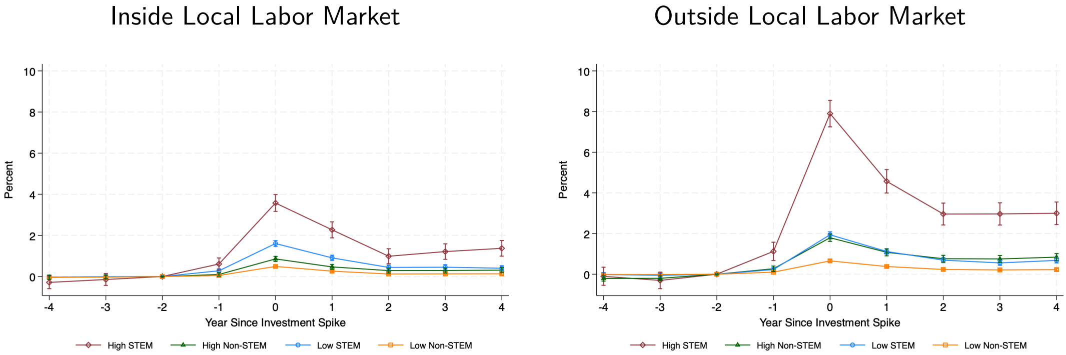


Capital-complementary skills: indivisible at the firm, smoothed across suppliers' clients

◂ Return ▸ Skill-Mix Stability ▸ Wage-Savings Motive

Local Labor Markets Miss Most of the External Skill Bias

External Employment from Machine Suppliers, % of Pre-spike by Skill



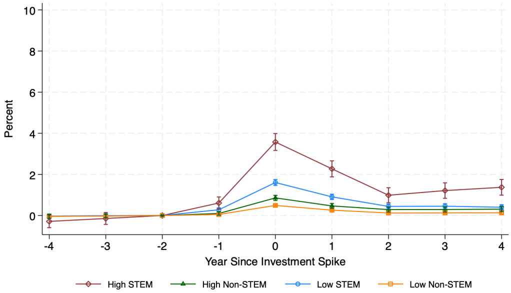
Notes: External employment from machine suppliers inside vs. outside the investing firm's local labor market (commuting zone).

◂ Additional Evidence ◂ Robustness ▸ Other Industries

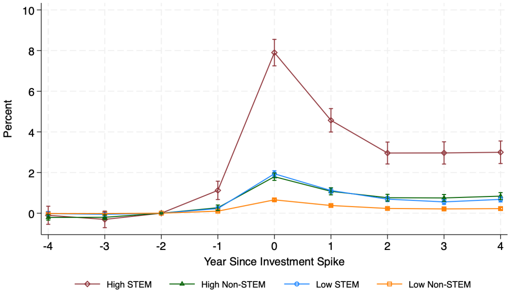
Local Labor Markets Miss Most of the External Skill Bias

External Employment from Machine Suppliers, % of Pre-spike by Skill

Inside Local Labor Market



Outside Local Labor Market

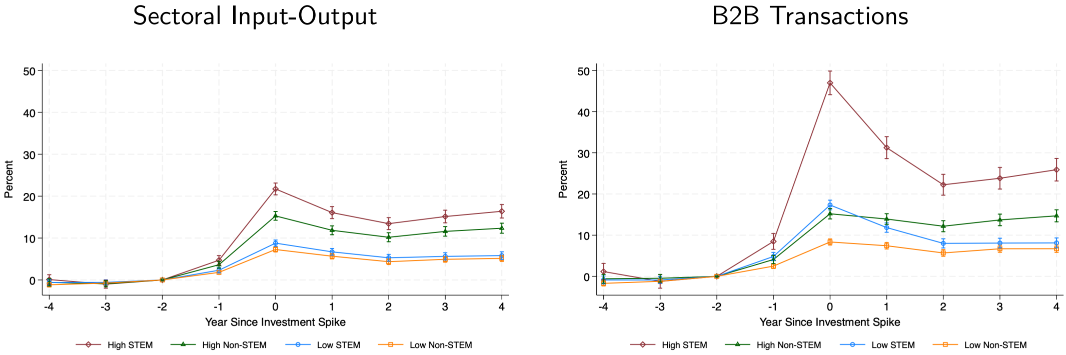


Much of the external skill bias is sourced from suppliers outside the local labor market

◂ Additional Evidence ◂ Robustness ▸ Other Industries

Sectoral Input-Output Misses Most of the External Skill Bias

External Employment as a Share of Total Pre-spike Employment by Skill



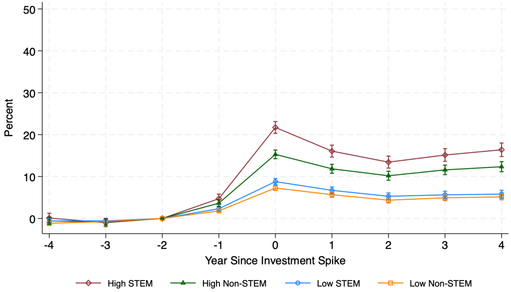
Notes: Panel (a) applies sectoral input-output tables to firm-level input purchases; Panel (b) uses firm-to-firm transactions (main results).

◂ Additional Evidence ◂ Robustness

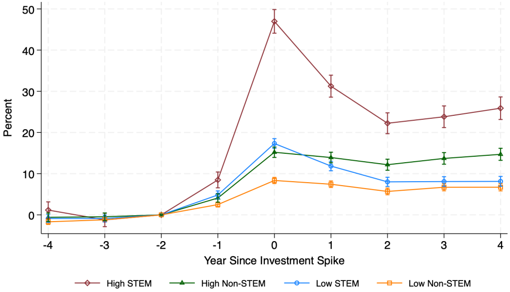
Sectoral Input-Output Misses Most of the External Skill Bias

External Employment as a Share of Total Pre-spike Employment by Skill

Sectoral Input-Output



B2B Transactions



External skill bias reflects a shift toward suppliers
that are more high-STEM-intensive than the industry average

◂ Additional Evidence ◂ Robustness