How do Workers Learn?
Theory and Evidence on the Roots of Lifecycle Human Capital Accumulation

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Motivation

Lifetime human capital has two main components: Schooling & **On-the-Job**

- Key for lifecycle earning dynamics & dispersion (Becker, 1962; Rubinstein and Weiss, 2006)
- Much less explored, particularly importance of different inputs

Literature: Individual inputs of "production function" of OTJ learning. Two categories:

1. **Internal learning** – coworkers, hierarchies, managers
   Garicano (2000); Garicano and Rossi-Hansberg (2004); Luttmer (2014); Akcigit et al. (2018); Herkenhoff et al. (2024); Jarosch et al. (2021); Caicedo et al. (2019)
2. **External learning** – external training, general population
   Acemoglu (1997); Acemoglu and Pischke (1998); Autor (2001); Lucas and Moll (2014); de la Croix et al. (2016)

This paper: How do **internal**/**external** learning jointly shape lifecycle human cap & wages, and the impacts of **remote work**?

Related Literature

Overview

1. **Empirics**: Use novel data to show both forms of learning matter for firms & workers:
   1. Worker-level data: **Internal learning** decreases with experience; **external learning** inverted U
   2. Firm-level data: Both **internal** & **external** provided by firms; larger firms offer more variety

2. **Quantitative model**: Dual-source learning in search framework a la CPVR (2006)
   - Key idea: **Internal** learning cheaper than **external**; but benefit of internal depleted faster

   $\Rightarrow$ Drives lifecycle results & predictions can be tested in data

   - Calibrate to US economy and find:

   1. **Internal learning** is key for overall (but especially early-career) human capital formation
   2. Spillover + learning cost effects explain 47% of lifecycle wage growth from human capital

   $\Rightarrow$ Non-own productivity aspects of human capital are key!

   3. Post-pandemic rise in **remote work** causes 5% decline in early-career wage growth

   $\Rightarrow$ But young workers substitute towards **external learning**

   $\Rightarrow$ Model with only one source of learning misstates the impact of **remote work**

Empirical Evidence

Internal & External Sources of On-the-Job Human Capital

Data: Learning sources across workers' lifecycles

German Data: Worker qualification data BIBB/BAuA in 1979–2018

- **Internal learning**: Acquired skills needed in current job through colleagues/superiors
- **External learning**: Acquired skills needed in current job through external training (e.g lectures/courses by external agents, visit trade fairs)

US Data: Adult education data from National Household Education Survey in 2016

- **Internal learning**: Received instruction from coworker in last work experience program
- **External learning**: Took external classes in last work experience program, or earned a certificate from an employer-sponsored training program

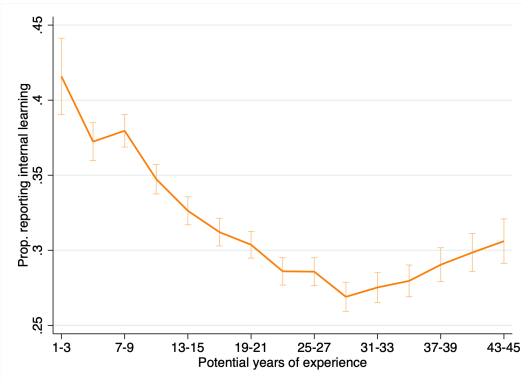
For both surveys:

- $\textit{Potential experience} = \textit{Age} - \textit{Years of schooling} - 6$
- Sample: Individuals who are currently working, and have 1–45 years of experience

Summary statistics Firm-level evidence

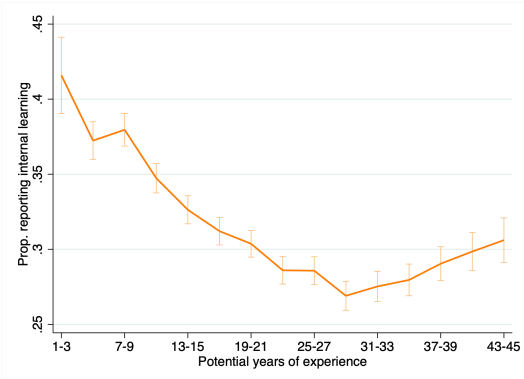
Results for Germany

(a) Internal learning

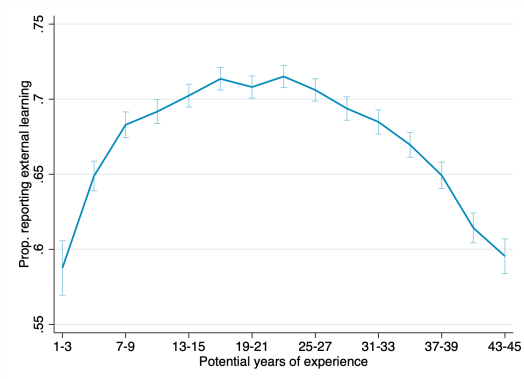


Results for Germany

(a) Internal learning



(b) External learning



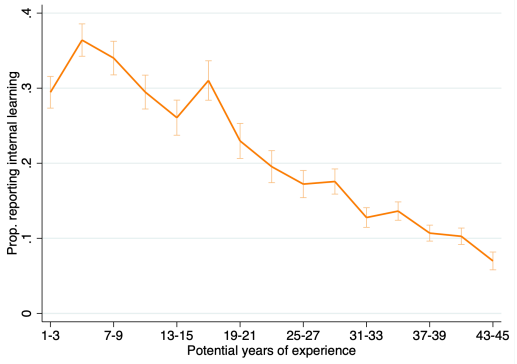
Notes: 95% confidence intervals plotted.

Table | Finer experience bins | By gender | By educational level | By firm size | By wave | By cohort | Correlation bw. sources

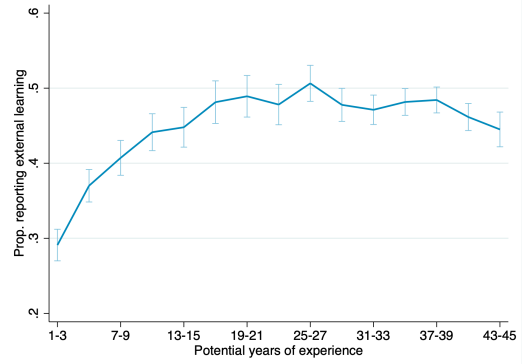
Alternate experience variables: Tenure current firm | Age

Results for the US

(a) Internal learning



(b) External learning



Notes: 95% confidence intervals plotted.

Table | Finer exp. bins | By gender | By education | Within work-exp. prog. | Finer EL Categ. | Correlation bw. sources

Alternate experience variables: Age

Additional evidence from other contexts: OECD–PIAAC | Custom SWAA data

Model

Role of Internal and External Learning on Lifecycle Dynamics

Setup: Embed dual learning mechanism in search framework

- Two sectors of production:
  1. Final goods: random search & wages a la Cahuc et al. (2006); heterogenous firms $z \sim \Phi(z)$
  2. Education: frictionless, unemployed can become trainers and sell external training
- Overlapping generations structure with finite lifetime and one unit of time per period
- Workers max expected lifetime earnings & accumulate human capital by climbing a ladder

$$h \in \{h_1, h_2, ..., h_M\}, \text{ where } h_M > ... > h_2 > h_1, \text{ and } \log(h_{m+1}) - \log(h_m) = \gamma_h \ \forall m.$$

- Three ways to climb ladder:
  1. **Internal learning**: observe random colleague in firm; cost = foregone production
  2. **External learning**: match with random trainer; cost = q + foregone production
  3. Learning-by-doing (exogenous probability, declines with human capital)
- Focus on stationary equilibrium

Prod. sectors Search

Learning requires higher-skill matches

– To learn **internal**/**external**, must match with colleague/trainer with higher human capital than own (Herkenhoff et al. (2024), Jarosch et al. (2021))

$$\underbrace{p(h_{m_i}, \mathbb{H}(z))}_{\text{Prob. internally learn at firm } z} = \underbrace{(1 - F(h_{m_i}; \mathbb{H}(z)))}_{\text{Share of coworkers w/ } h > h_{m_i} \text{ in firm } z}$$

$$\underbrace{p_e(h_{m_i})}_{\text{Prob externally learn}} = \underbrace{(1 - F_t(h_{m_i}))}_{\text{Share of training units produced by trainer w/ } h > h_{m_i}}$$

– $\mathbb{H}(z)$ denotes the human capital distribution of firm z's workforce

Human capital accumulation

- Workers born with $h_1 = 1$
- Workers allocate time to work, **internal learning** and **external learning**
  - l: total time spent learning (both modes)
  - g: share of l spent **internal learning** (v. **external learning**)
- **Probability of climbing human capital ladder**:

$$s(h_{m_i}, \mathbb{H}(z)) = \min\left(\left[\underbrace{(A(z)p(h_{m_i}, \mathbb{H}(z))g)^{\frac{\sigma-1}{\sigma}}}_{\text{Internal learning component}} + \underbrace{(A_e(z)p_e(h_{m_i})(1-g))^{\frac{\sigma-1}{\sigma}}}_{\text{External learning component}}\right]^{\frac{\sigma}{\sigma-1}} l^{\gamma} + \underbrace{\epsilon_{m_i}}_{\text{LBD}}, 1\right)$$

- LBD probability declines with human capital: $\epsilon_{m_i} = \epsilon\, e^{-\delta_\epsilon m_i}$, $\delta_\epsilon > 0$
- Human capital depreciates; probability of climbing down ladder: $p_{descend}(h_{m_i}) = \frac{\delta_h(h_{m_i} - h_1)}{h_{m_i} - h_{m_i - 1}}$

Learning, wage, and vacancy determination

- Output of match between firm z and worker i: $y = zh_{m_i}$
- Worker jointly decides **internal**/**external** learning with firm to maximize match value >
- Wage each period proportional to current match revenue, with fraction accruing to worker (piece rate) determined upon hiring via Nash Bargaining to max match surplus > (Cahuc et al., 2006)
- Each firm chooses vacancies to maximize its share of surplus from hiring workers >

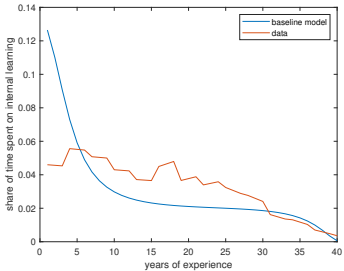
Calibration

- Model period = quarter; calibrated to US
- Two sets of parameters:
  1. Externally calibrated following literature >
  2. Internally calibrated List of moments Parameter values
- Key moments informing learning:
  - Shares of time spent on internal & external learning (US-SEPT)
  - Time spent on learning in medium v. large firms, and old v. rest workers (US-SEPT)
  - Wage returns from experience attributed to human capital when young & overall
  - Participation on external learning by young v. rest workers (NHES)

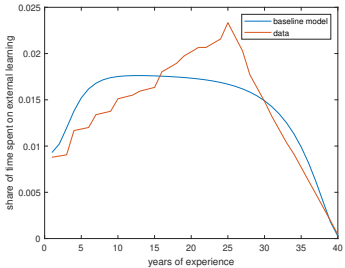
US-SEPT

Model matches lifecycle patterns

(a) Internal learning



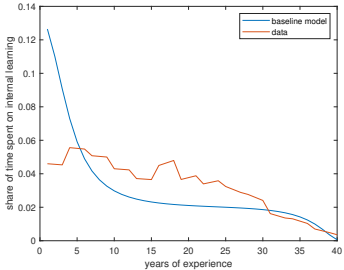
(b) External learning



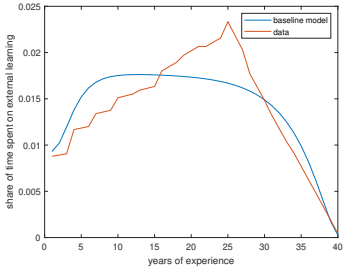
Notes: Total time spent on each source of learning, $l \times g$ and $l \times (1 - g)$, in model and data.

Model matches lifecycle patterns

(a) Internal learning



(b) External learning



Notes: Total time spent on each source of learning, $l \times g$ and $l \times (1-g)$, in model and data.

- **Counterfactuals**: Avg h falls 6.6% w/o **external**, 8.2% w/o **internal**
  $\Rightarrow$ **Internal** key during youth, **external** later >
- **Wages**: Spillovers + learning costs explain 47% of lifecycle wage growth from HC
  $\Rightarrow$ Non-own productivity aspects of human capital are key >

Testable predictions | Additional exercises and robustness

Remote Work Exercise

How Does Post-Pandemic Remote Work Landscape Affect Learning and Wages?

Assess impacts of post-pandemic remote work landscape

- Shock to **internal learning** using findings from literature:
  - Barrero et al. (2021): Share of remote working days rose from 5% to 20% after the pandemic
  - Emanuel et al. (2023): 15% reduction in feedback from adjacent coworkers after remote work

  $\Rightarrow$ 2.25% decrease in success rate of internal learning ($15\% \times 15\%$)
- Also study 100% remote work scenario & 14.25% drop in success rate ($95\% \times 15\%$)

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		Impact of remote work (rel. to baseline)	
	Baseline	20% remote work	100% remote work
Avg human capital	1.22	-0.37%	-2.93%
Δ log wage, 0–5 yrs of exp	0.255	-4.99%	-26.62%

$\Rightarrow$ **Young** workers' wage loss stems from lower own productivity due to less senior mentoring

$\Rightarrow$ Long-lasting: young workers who learn less are less equipped to mentor future cohorts

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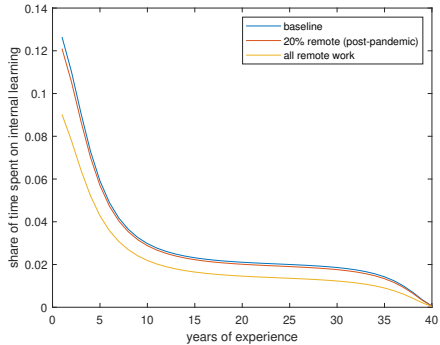
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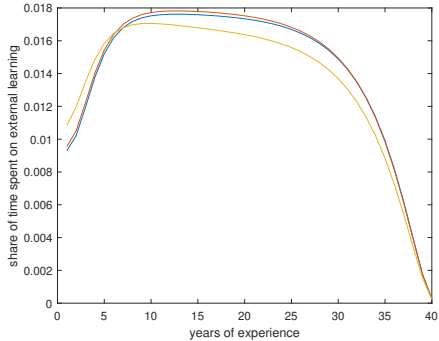
$\Rightarrow$ But, this loss is mitigated as young workers substitute towards **external learning**

Learning decline partially offset thru external learning

(a) Internal learning



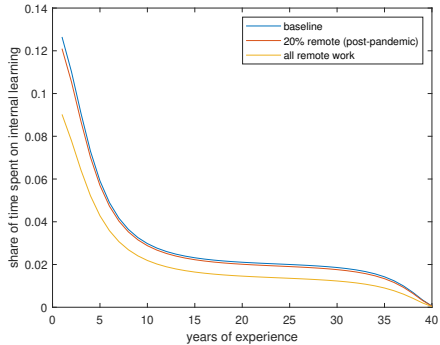
(b) External learning



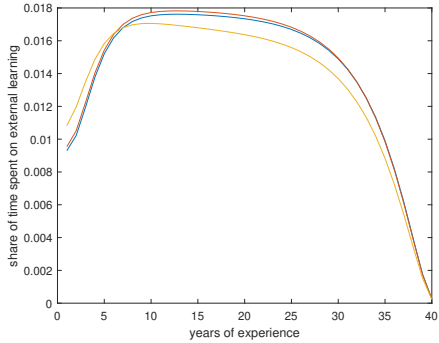
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Learning decline partially offset thru external learning

(a) Internal learning



(b) External learning



Notes: These figures depict total time spent on each source of learning, namely $l \times g$, and $l \times (1 - g)$.

Both learning sources are needed to understand impact of remote work!

- W/o **internal learning**: remote work has *no* effect on h or wages
- W/o **external learning**: h loss overstated since workers can't replace lost mentoring

Evidence of shift from internal to external learning due to remote work

Use two datasets: **SWAA** and **PIAAC**

- **SWAA Data**: Custom worker learning module fielded in Dec 2023 within the *Survey of Working Arrangements and Attitudes (SWAA)* (Barrero et al., 2021) >

⇒ Asks how internal/external learning changed *relative to 2019* (pre-Covid)

- **PIAAC Data**: Survey on learning & skills of workers 16–65 in OECD, conducted in 2011–2017 (pre-Covid) & 2022–2023 (post-Covid) >

⇒ Has larger sample + rich occupation info so can use IV with *occupation-based telework suitability* (Dingel and Neiman, 2020)

Results for SWAA

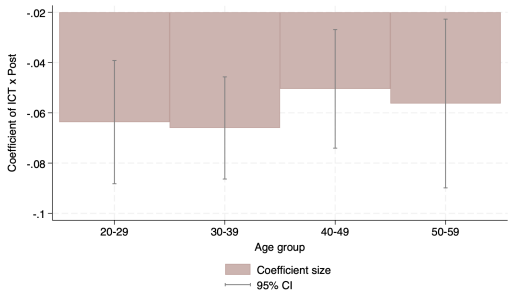
Specification: Regress changes in internal/external learning since 2019 on share of days worked remotely last week

	Young workers (≤25)		Old workers (>25)	
	Int. learning	Ext. learning	Int. learning	Ext. learning
Worked remotely > 25% of last week	-0.171**	0.140*	0.0198	0.0205
	(0.0813)	(0.0801)	(0.0193)	(0.0176)
Constant	0.147***	0.0783***	0.0729***	0.0568***
	(0.0246)	(0.0242)	(0.00676)	(0.00614)
Observations	236	236	2,510	2,510
R-squared	0.576	0.586	0.106	0.096
Demographic controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Occupation FE	Y	Y	Y	Y
Firm size FE	Y	Y	Y	Y
Wage controls	Y	Y	Y	Y

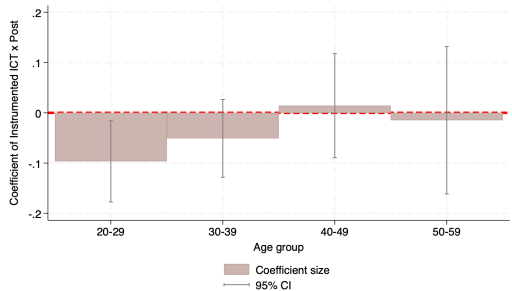
Results for PIAAC

Specification: Regress internal learning in 2011–2017 (pre-Covid) & 2022–2023 (post-Covid) on index of ICT use at work (proxy for remote work exposure) using DiD and IV-DiD

(a) DiD



(b) IV-DiD



Conclusions

Consider **internal** & **external** learning for on-the-job human capital and wage growth

Document: **Internal learning** decreases with experience; **external learning** inverted U-shape

Theory and quantitative evidence of learning from **internal** & **external** sources

- **Lifecycle mechanism**: Benefit of **internal** exhausted quicker; but cheaper than **external**

$\Rightarrow$ Drives lifecycle results & predictions tested in data

- **Calibrated to US economy**

$\Rightarrow$ Match empirical patterns of lifecycle of learning & more variety of learning in large firms

$\Rightarrow$ **Internal learning** is key for overall (but especially early-career) human capital formation

$\Rightarrow$ **Remote work** hurts wages of young workers; but **external learning** helps

Appendix

Related Literature

- **Peer learning**
  - Within coworker teams (Nix (2017), Akcigit et al. (2018), Herkenhoff et al. (2024), Jarosch et al. (2021), Caicedo et al. (2019), Emanuel et al. (2023))
  - Within the population at large (Glaeser (1999), Lucas and Moll (2014), Perla and Tonetti (2014) and de la Croix et al. (2016))
- **Training**
  - Theory of on-the-job training (Becker (1964), Acemoglu (1997), Acemoglu and Pischke (1998), Acemoglu and Pischke (1999), Autor (2001))
  - Impact of training programs on human capital accumulation and earnings (Mincer (1988), Altonji and Spletzer (1991), Loewenstein and Spletzer (1999), Booth and Bryan (2005), Konings and Vanormelingen (2015))

Our contribution:

- New theory that combines these two sources of learning
- Empirically show coexistence and lifecycle patterns of learning sources within workers

– **Interaction between learning and lifecycle dynamics:** (Bunzel et al. (1999); Rubinstein and Weiss (2006); Barlevy (2008); Yamaguchi (2010); Burdett et al. (2011); Bowlus and Liu (2013); Bagger et al. (2014); Gregory (2019))

– **Role of firm characteristics on workers' human capital accumulation and earnings dynamics** (Gregory (2019), Arellano-Bover (2020), Engbom (2021), Friedrich et al. (2021), Jarosch (2022), Engbom et al. (2022))

Back

Our contribution:

– Quantify importance of each source in human capital

– Emphasis on tradeoff between work and learning

– Highlight importance of non-own productivity aspects of human capital in worker compensation

Our contribution:

– Variety in learning opportunities (internal & external) is key driver of firms' learning environments

Other inputs in worker's human capital accumulation:

- Worker's time investments (work/learn tradeoff) (Ben-Porath (1967))
- Learning-by-doing (Bagger et al. (2014) and Gregory (2019))
- Knowledge hierarchies (Garicano (2000); Garicano and Rossi-Hansberg (2004, 2006),Caicedo et al. (2019))
- Managerial inputs (Burstein and Monge-Naranjo (2009))
- Complementary goods (Manuelli and Seshadri (2014))

Back

Firms' provision of internal and external learning

Data: European Union Continuing Vocational Training (CVT) Survey

- Information on types of learning, content and use of own/external training providers
- Three waves: 2005, 2010, and 2015

Variables of Interest:

- *Internal CVT*: Firm offers courses, seminars or activities that take place inside the firm and employ internal trainers
- *External CVT*: Firm offers courses, seminars or activities that take place outside the firm or employ external trainers
- *Other types of CVT Activities*: Firm offers less organized learning activities of different types
  (some internal and some external)

- **Internal learning**: Firm offers internal CVT or other internal CVT activities
- **External learning**: Firm offers external CVT or other external CVT activities

Empirical evidence: Larger firms offer greater variety in learning

Table: Share of firms providing internal and external learning activities by firm size

Small firms, 5–19 wk.				Medium firms, 20–99 wk.				Large firms, 100+ wk.			
		External learning				External learning				External learning	
		0	1			0	1			0	1
Internal learning	0	0.42	0.16	Internal learning	0	0.28	0.15	Internal learning	0	0.13	0.09
	1	0.11	0.31		1	0.11	0.45		1	0.07	0.71

Table Hours of learning by type and firm size Share of all firms Evidence from US
Back

Share of firms providing different CVT types by country

Country	CVT courses		Other types of CVT activities			
	Internal CVT courses	External CVT courses	Conferences, workshops or lectures	Guided on-the-job training	Job rotation	Learning and quality circles
Germany	0.436	0.532	0.438	0.524	0.085	0.151
France	0.329	0.666	0.193	0.253	0.094	0.082
United Kingdom	0.418	0.532	0.399	0.655	0.204	0.218
Italy	0.263	0.403	0.263	0.260	0.100	0.035
Spain	0.186	0.564	0.198	0.354	0.108	0.127
...						
Total	0.275	0.433	0.242	0.328	0.101	0.091

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Correlations between provision of sources of learning and firm size

	CVT	Internal CVT	External CVT
Firm size: 20–49	0.117***	0.109***	0.121***
	(0.006)	(0.006)	(0.006)
Firm size: 50–99	0.199***	0.200***	0.228***
	(0.007)	(0.008)	(0.008)
Firm size: 100–250	0.280***	0.304***	0.325***
	(0.006)	(0.007)	(0.007)
Firm size: 250+	0.293***	0.372***	0.350***
	(0.007)	(0.007)	(0.007)
Observations	286,321	286,321	286,321
R-squared	0.179	0.160	0.170
Country-Year FE	Y	Y	Y
Industry FE	Y	Y	Y
Socioec. controls	Y	Y	Y

Omitted category: Firm with 5–19 workers.

Back

Average number and share of hours spent by each worker on CVT courses by firm size

	CVT courses	Internal CVT courses	External CVT courses
	Panel A: Average share of working hours		
Small firms, 5–19 workers	0.0027	0.0011	0.0016
Medium firms, 20–99 workers	0.0037	0.0015	0.0022
Large firms, 100+ workers	0.0058	0.0028	0.0030
Total	0.0040	0.0018	0.0023
	Panel B: Average number of hours per worker		
Small firms, 5–19 workers	4.861	2.006	2.855
Medium firms, 20–99 workers	6.077	2.451	3.626
Large firms, 100+ workers	9.491	4.505	4.987
Total	6.550	2.834	3.716

Back

Share of firms providing internal and external learning activities

		External learning	
		0	1
Internal learning	0	0.33	0.15
	1	0.11	0.41

Share of firms by CVT type by country Back

Evidence on firms' provision of learning in the US

US Data: Survey of Employer-Provided Training (SEPT) in 1995

- Enterprise-level survey focusing on firms with 50+ workers across industries & states
- External & internal learning can be roughly matched to formal & informal training
  - Formal training: Structured training that is planned in advance (e.g classes/seminars)
  - Informal training: Unstructured & adaptable training (e.g learn from coworker/supervisor)

	Informal training	Formal training
	Panel A: Share of workers who have received training with current employer	
Small firms, 50–99 workers	78.9	97.1
Medium firms, 100–499 workers	84.7	95.0
Large firms, 500+ workers	87.7	96.1
	Panel B: Average number of hours per worker	
Small firms, 50–99 workers	8.2	31.9
Medium firms, 100–499 workers	13.5	34.5
Large firms, 500+ workers	16.6	26.0

Summary statistics

	Germany		United States	
	Mean	Std. dev.	Mean	Std. dev.
Reports internal learning	0.31	0.46	0.23	0.42
Reports external learning	0.68	0.47	0.44	0.5
Woman	0.42	0.49	0.52	0.5
Age	40.2	11.2	41	12.05
Years of education	10.8	2.7	14.6	12.1
Potential years of experience	23.4	11.6	20.7	12.5
Years with current employer	11.3	9.9		
Hourly wage (Euros of 2015/Dollars of 2016)	8.96	9.07	27.34	37.93
Firm size 1–9	0.23	0.42		
Firm size 10–99	0.37	0.48		
Firm size 100+	0.4	0.49		
Observations	$\sim$ 170,000		$\sim$ 30,000	

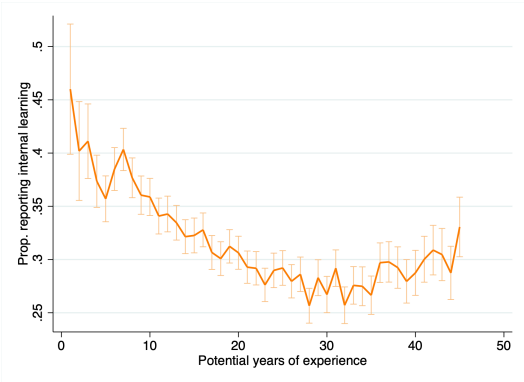
Correlations between learning sources and experience in Germany

	Internal learning		External learning	
Potential yrs. experience	-0.0104***	-0.00312***	0.0105***	0.00216***
	(0.000672)	(0.000798)	(0.000552)	(0.000520)
Potential yrs. experience^2	0.000167***	4.34e-05***	-0.000247***	-6.66e-05***
	(1.37e-05)	(1.69e-05)	(1.14e-05)	(1.07e-05)
Observations	109,478	36,813	173,391	85,280
R-squared	0.006	0.071	0.005	0.191
Year FE		Y		Y
Demographic controls		Y		Y
Worker Type FE		Y		Y
Industry FE		Y		Y
Occupation FE		Y		Y
Firm size FE		Y		Y
Wage controls		Y		Y

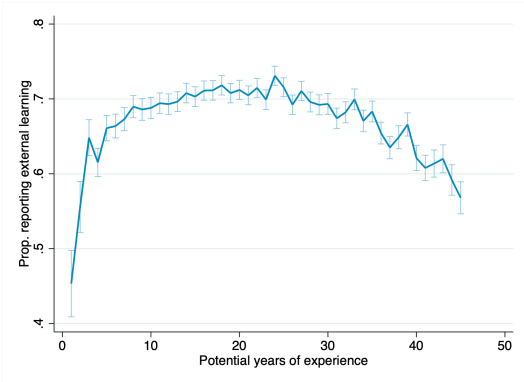
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Finer experience bins for Germany

(a) Internal learning



(b) External learning



Notes: 95% confidence intervals plotted.

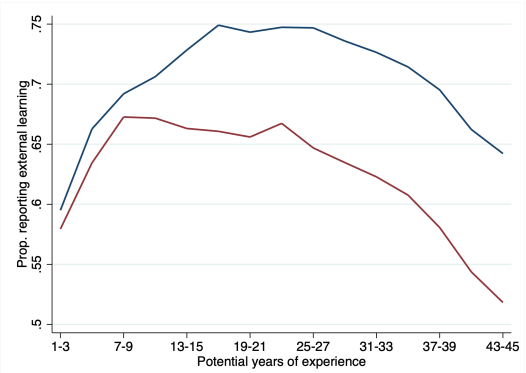
Back

Results by gender for Germany

(a) Internal learning



(b) External learning

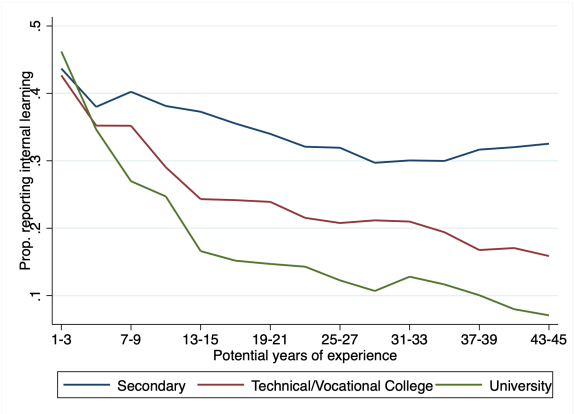


Notes: Confidence intervals omitted for clarity.

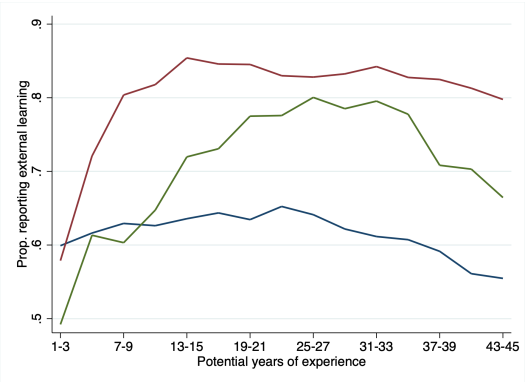
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Results by educational attainment for Germany

(a) Internal learning



(b) External learning

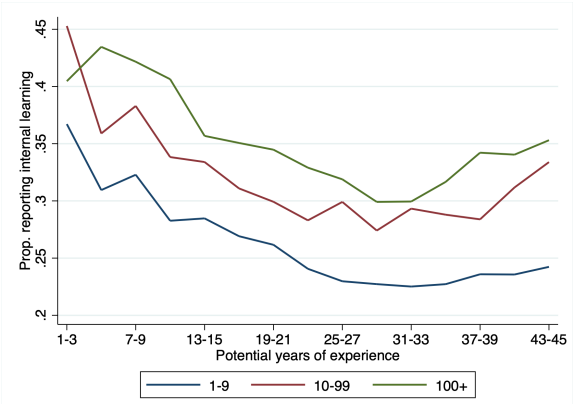


Notes: Confidence intervals omitted for clarity.

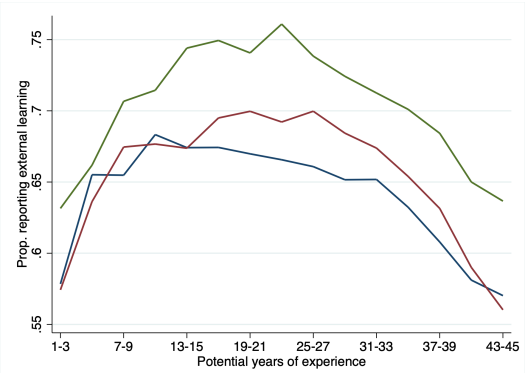
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Results by firm size for Germany

(a) Internal learning



(b) External learning

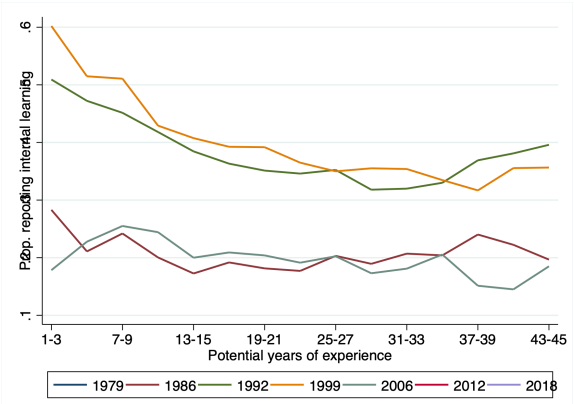


Notes: Confidence intervals omitted for clarity.

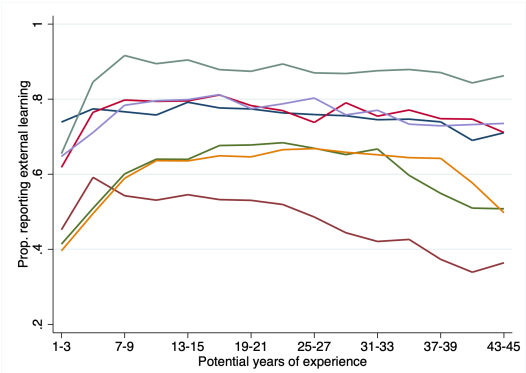
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Results by wave for Germany

(a) Internal learning



(b) External learning

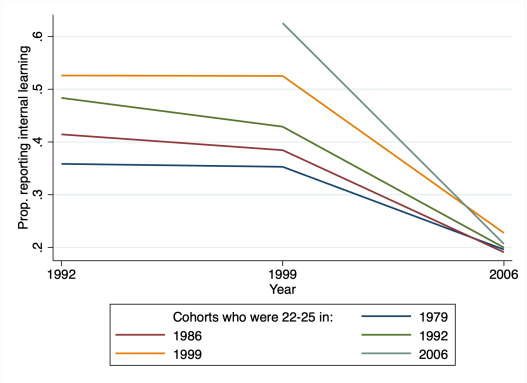


Notes: Confidence intervals omitted for clarity.

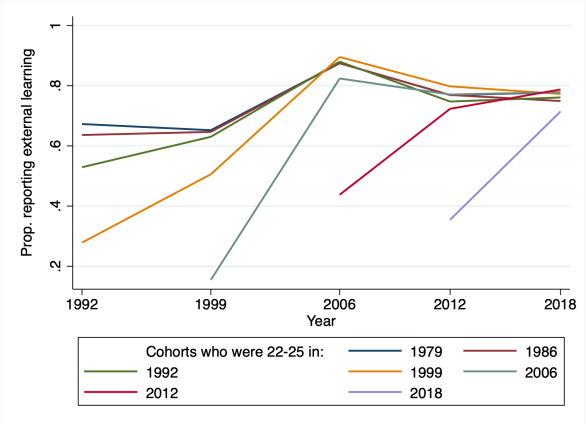
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Results by cohort for Germany

(a) Internal learning



(b) External learning



Notes: Due to comparability and data availability issues across waves, these figures rely on learning data from 1992 to 2006 (internal learning), and 1992 to 2018 (external learning). Confidence intervals omitted for clarity.

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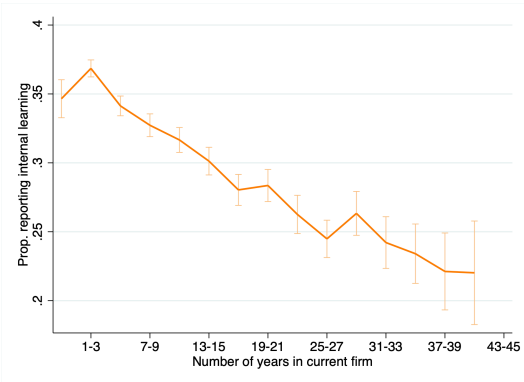
Correlation between learning sources in Germany

	Internal learning		
External learning	-0.20***	-0.15***	-0.15***
	(0.004)	(0.005)	(0.006)
Observations	109,478	69,495	36,813
R-squared	0.05	0.15	0.10
Year FE		Y	Y
Demographic controls		Y	Y
Age FE		Y	Y
Worker type FE		Y	Y
Industry FE		Y	Y
Occupation FE		Y	Y
Firm size FE		Y	Y
Wage controls			Y

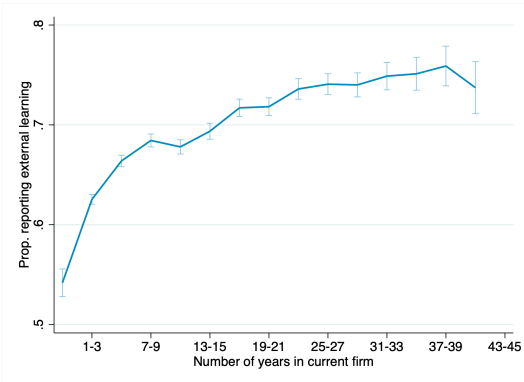
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Prevalence of learning sources by tenure in the current firm in Germany

(a) Internal learning



(b) External learning

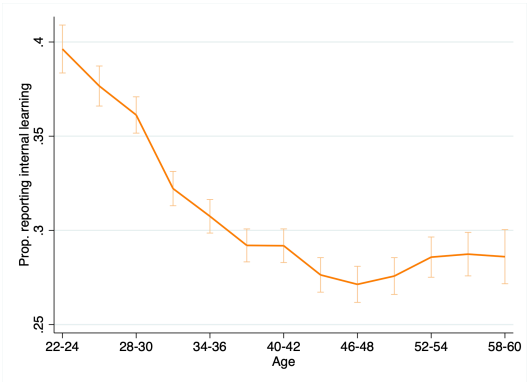


Notes: 95% confidence intervals plotted.

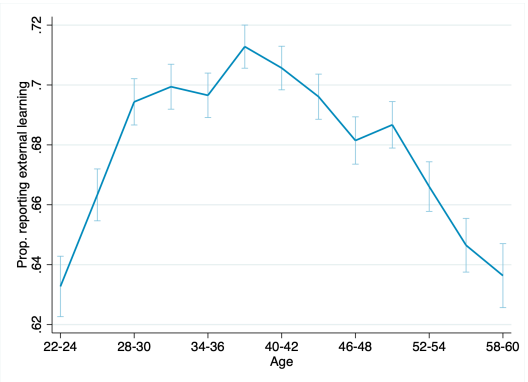
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Prevalence of learning sources by age in Germany

(a) Internal learning



(b) External learning



Notes: 95% confidence intervals plotted.

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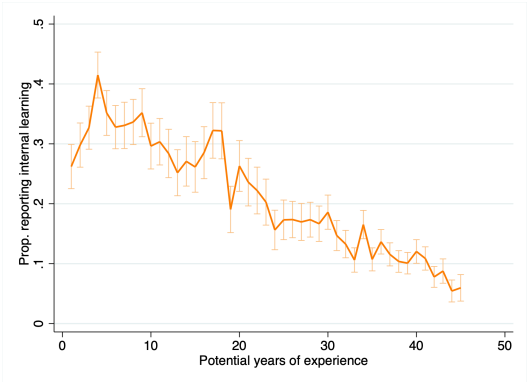
Correlations between learning sources and experience in the US

	Internal learning		External learning	
Potential yrs. experience	-0.00489***	-0.00999***	0.0153***	0.0114***
	(0.00120)	(0.00105)	(0.00141)	(0.00142)
Potential yrs. experience^2	-4.13e-05*	0.000110***	-0.000277***	-0.000188***
	(2.49e-05)	(2.17e-05)	(3.05e-05)	(3.08e-05)
Observations	29,217	27,585	29,217	27,585
R-squared	0.040	0.224	0.013	0.075
Demographic controls		Y		Y
Worker Type FE		Y		Y
Industry FE		Y		Y
Occupation FE		Y		Y
Wage controls		Y		Y

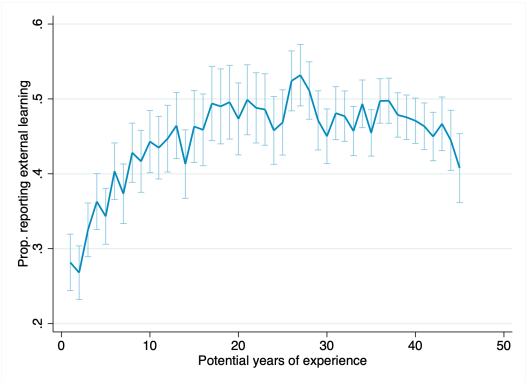
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Finer experience bins for the US

(a) Internal learning



(b) External learning

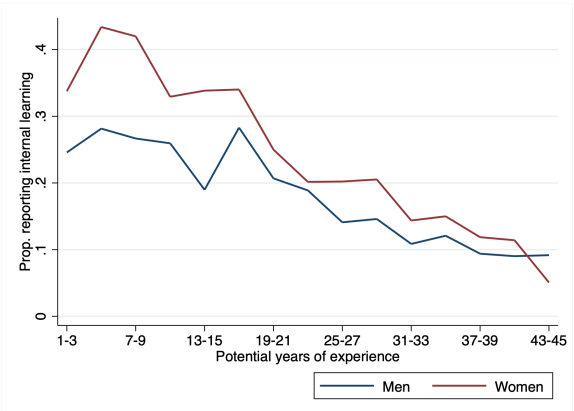


Notes: 95% confidence intervals plotted.

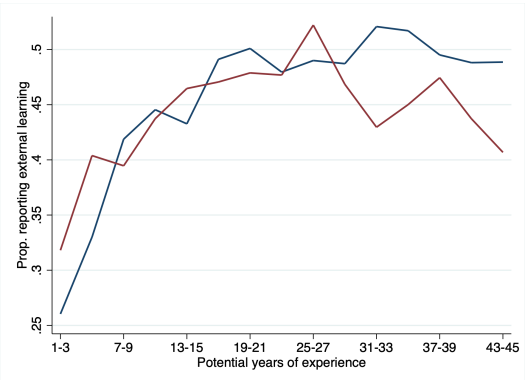
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Results by gender for the US

(a) Internal learning



(b) External learning

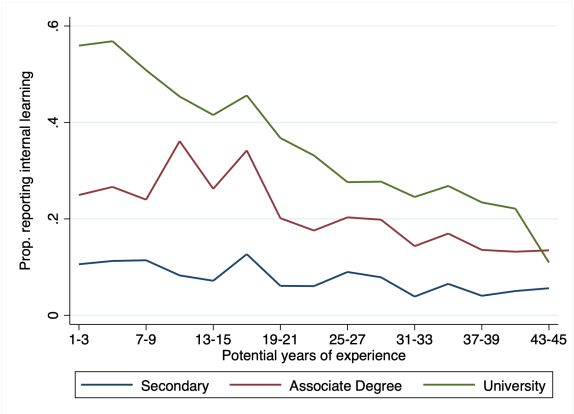


Notes: Confidence intervals omitted for clarity.

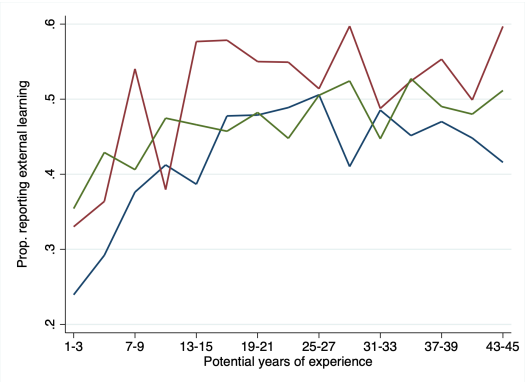
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Results by educational attainment for the US

(a) Internal learning



(b) External learning

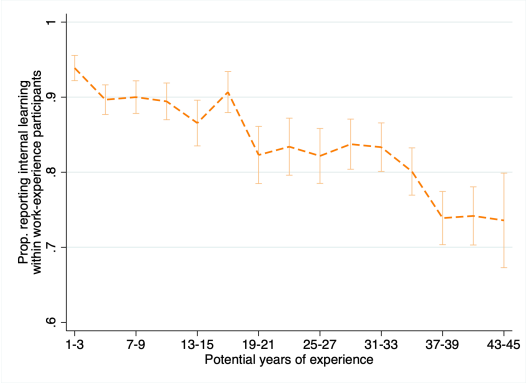


Notes: Confidence intervals omitted for clarity.

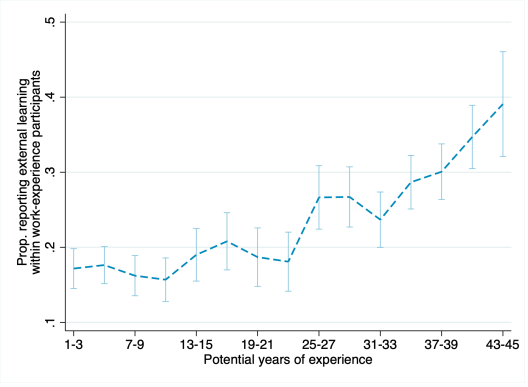
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Prevalence of learning for workers reporting participating in a work-experience program in the US

(a) Internal learning



(b) External learning

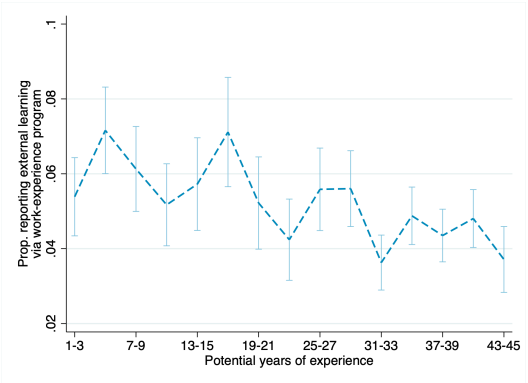


Notes: 95% confidence intervals plotted.

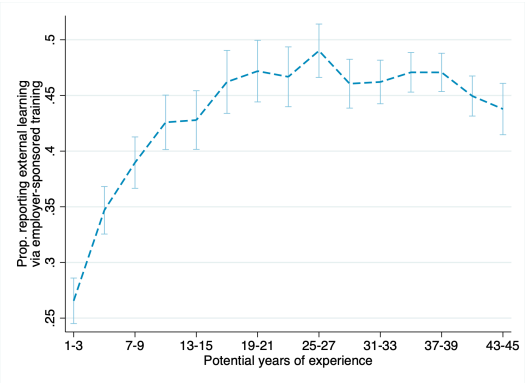
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Prevalence of external learning by type in the US

(a) On-the-job training via participation in work-experience program



(b) On-the-job training via certificate in employer-sponsored training



Notes: 95% confidence intervals plotted.

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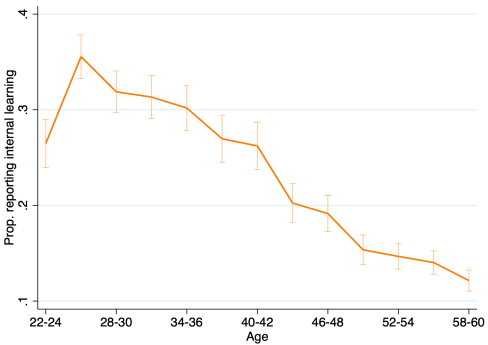
Correlation between learning sources in the US

	Internal learning		
External learning	0.10***	0.09***	0.09***
	(0.008)	(0.007)	(0.007)
Observations	29,399	29,399	27,767
R-squared	0.01	0.24	0.24
Demographic controls		Y	Y
Age FE		Y	Y
Worker type FE		Y	Y
Industry FE		Y	Y
Occupation FE		Y	Y
Wage controls			Y

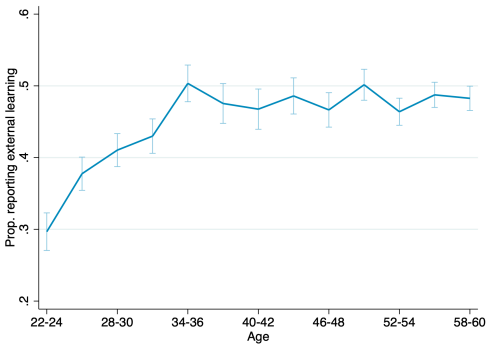
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Prevalence of learning sources by age in the US

(a) Internal learning



(b) External learning



Notes: 95% confidence intervals plotted.

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Evidence on lifecycle patterns of learning in OECD

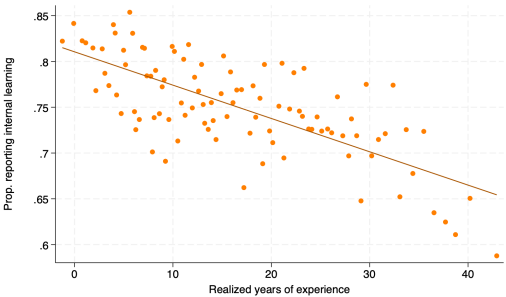
PIAAC Data: Survey on learning & skills of workers 16–65 in OECD, conducted in 2011–2017

- **Internal learning**: Participated in courses led by coworkers/supervisors last 12 months; or reports learning skills from coworkers often in current work
- **External learning**: Participated in courses led by outsiders in last 12 months
- Realized years of experience: Years of paid work (6+ months in year)
- Sample: Individuals who are currently working, and have 1–45 years of realized & potential experience

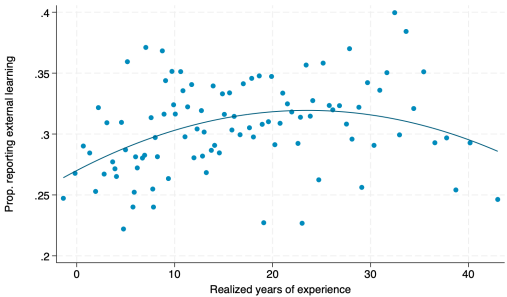
Countries in analysis Summary statistics

Results for OECD; Binned scatterplots

(a) Internal learning



(b) External learning



Notes: These binned scatterplots plot the proportion of workers reporting engaging in internal and external learning across different realized years of experience bins in the PIAAC data using pooled data from all countries considered and controlling for country fixed effects.

Table | Results with potential experience | Back

OECD Countries used in data analysis

- **Round 1 (2011–2012):** Czech Republic, Denmark, Estonia, Finland, France, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russia, Slovakia, Spain, Sweden, and the UK.
- **Round 2 (2014–2015):** Chile, Greece, Israel, Lithuania, Slovenia, and Turkey.
- **Round 3 (2017):** Ecuador, Kazakhstan, Mexico, and Peru.

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Summary statistics in PIAAC data

	Mean	Std. dev.	Minimum	Maximum	# Obs.
Reports internal learning	0.75	0.43	0	1	55112
Reports external learning	0.31	0.46	0	1	60244
Woman	0.46	0.5	0	1	60274
Age	39.87	11.06	19	65	60275
Years of education	14.48	2.41	12	23	60275
Realized years of experience	16.56	10.81	1	45	60275
Potential years of experience	19.4	11.25	1	45	60275
Hourly wage (Dollars of survey year, PPP)	18.76	156.24	0	55411.45	49624
Firm size: 1–10 workers	0.3	0.46	0	1	53620
Firm size: 11–250 workers	0.52	0.5	0	1	53620
Firm size: 251+ workers	0.18	0.39	0	1	53620

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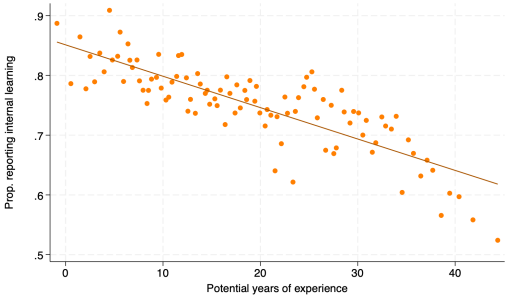
Correlations between learning sources and experience in OECD

	Internal learning			External learning		
Realized yrs. experience	-0.000834	-0.00432***	-0.00512***	0.00477***	0.00177	0.00148
	(0.00123)	(0.00121)	(0.00130)	(0.00108)	(0.00115)	(0.00126)
Realized yrs. experience^2	-7.28e-05**	-4.07e-06	1.09e-05	-0.000103***	-3.97e-05	-3.06e-05
	(3.15e-05)	(3.06e-05)	(3.31e-05)	(2.67e-05)	(2.83e-05)	(3.10e-05)
Observations	55,112	47,430	40,268	60,244	47,448	40,282
R-squared	0.043	0.121	0.123	0.051	0.159	0.158
Country FE	Y	Y	Y	Y	Y	Y
Demographic controls		Y	Y		Y	Y
Worker type FE		Y	Y		Y	Y
Industry FE		Y	Y		Y	Y
Occupation FE		Y	Y		Y	Y
Firm size FE		Y	Y		Y	Y
Wage controls			Y			Y

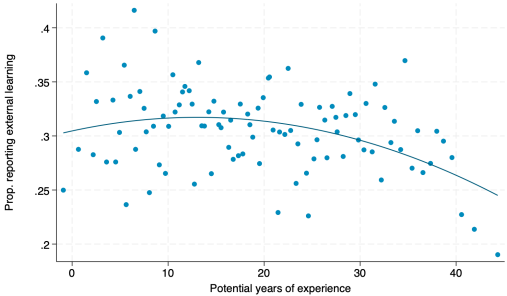
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Results for OECD with potential experience; Binned scatterplots

(a) Internal learning



(b) External learning



Notes: These binned scatterplots plot the proportion of workers reporting engaging in internal and external learning across different potential years of experience bins in the PIAAC data using pooled data from all countries considered and controlling for country fixed effects.

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Evidence on lifecycle patterns of learning from custom module in SWAA

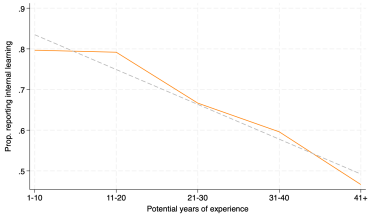
SWAA Data: Custom worker learning module fielded in Dec 2023 within the *Survey of Working Arrangements and Attitudes (SWAA)* (Barrero et al., 2021)

- **Internal learning**: Reported spending time in the past month being mentored, discussing their performance with a supervisor, or attending training sessions led by colleagues or managers.
- **External learning**: Reported spending time in the past month attending training sessions led by persons outside their workplace or engaging in self-learning using external materials
- Also have **perceived usefulness**: worker reports using knowledge acquired through each source *more often than monthly* in current job
- Sample: Individuals who are currently working, have 1–45 years of potential experience, passed all attention checks, do not work fully remotely

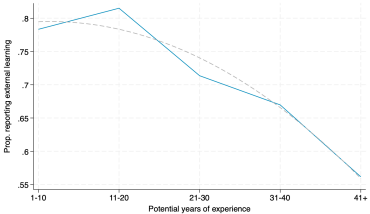
Summary statistics

Results for SWAA

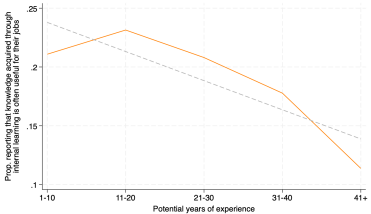
(a) Internal learning



(b) External learning



(c) Internal learning is often useful



(d) External learning is often useful

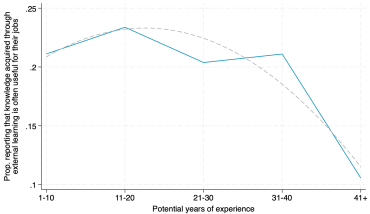


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Summary statistics in SWAA data

	Mean	Std. dev.	Minimum	Maximum	# Obs.
Reports internal learning	0.70	0.46	0	1	3118
Reports external learning	0.74	0.44	0	1	3118
Reports internal learning is often useful	0.21	0.4	0	1	1092
Reports external learning is often useful	0.21	0.41	0	1	1030
Reports more internal learning rel. to 2019	0.08	0.28	0	1	3118
Reports more external learning rel. to 2019	0.07	0.26	0	1	3118
Share of days worked remotely last week	0.15	0.27	0	1	3061
Woman	0.49	0.50	0	1	3118
Age	42.09	12.11	20	67	3118
Years of education	14.54	2.14	12	21	3118
Potential years of experience	21.55	11.96	1	45	3118
Hourly wage (Dollars of 2019)	38.39	107.60	0.6	6666.67	3118
Firm size: 1–9 workers	0.08	0.28	0	1	2915
Firm size: 10–99 workers	0.36	0.48	0	1	2915
Firm size: 100+ workers	0.56	0.50	0	1	2915

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Correlations between learning sources and experience in SWAA

	Internal learning			External learning		
Potential yrs. exper.	-0.000858	-0.00119	-0.00125	0.00103	0.00126	0.00119
	(0.00264)	(0.00270)	(0.00270)	(0.00257)	(0.00261)	(0.00261)
Potential yrs. exper.^{2}	-0.000165***	-0.000122**	-0.000121**	-0.000148***	-0.000113**	-0.000112*
	(5.88e-05)	(5.96e-05)	(5.96e-05)	(5.72e-05)	(5.78e-05)	(5.78e-05)
Constant	0.820***	0.821***	0.818***	0.805***	0.781***	0.777***
	(0.0255)	(0.0259)	(0.0260)	(0.0248)	(0.0251)	(0.0252)
Observations	3,118	2,903	2,903	3,118	2,903	2,903
R-squared	0.047	0.165	0.165	0.024	0.184	0.184
Demographic controls		Y	Y		Y	Y
Industry FE		Y	Y		Y	Y
Occupation FE		Y	Y		Y	Y
Firm size FE		Y	Y		Y	Y
Wage controls			Y			Y

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Production and Training sectors

- **Production sector**
  - Frictional labor market: random search & wage determination a la Cahuc et al. (2006)
  - Measure of heterogenous firms; draw productivity $z \sim \Phi(z) = 1 - z^{-\zeta}$
  - Output produced by match between firm z and worker i: $y = zh_{m_i}$

- **Training sector**
  - Frictionless sector: unemployed workers can choose to become trainers
  - Training services are provided to production workers
    - Workers randomly meet trainers & decide to acquire services after observing trainer type
    - Decision depends on whether worker can learn from trainer
  - Trainer i produces h_{m_i} units of training

$$\underbrace{E(w_e(h_{m_i}))}_{\text{Expected Trainer Wage}} = \underbrace{h_{m_i}}_{\text{Units of training produced}} \times \underbrace{F_e(h_{m_i-1})}_{\text{Fraction of trainees with } h < h_{m_i}} \times \underbrace{q}_{\text{Cost of training service}}$$

Back

Search and matching in production sector

- **Unemployed workers** U
  - Job destruction: probability κ of job-to-unemployment
  - Young workers are born unemployed
  - Trainers who decide to join production sector

- **Vacancies**
  - Firms post vacancies v per period with costs $\frac{c_v v^{1+\gamma_v}}{1+\gamma_v}$, $\gamma_v > 0$
  - Total vacancies: $V = \int v(z) d\Phi(z)$

- **Matching**
  - Matching function: $M(U, V) = c_M V^{1-\phi} U^{\phi}$
  - Market tightness $\theta = \frac{V}{U}$

Back

Derivation of match value

- If didn't have internal learning/spillovers, match value would be

$$M^{a_i}(h_{m_i}, z, \mathbb{H}(z)) = \max_{l,g} \Bigg[\underbrace{z h_{m_i}(1-l)}_{\text{output value}} - \underbrace{(1-g)l \times q p_e(h_{m_i})}_{\text{pay external train.}} + \underbrace{s(h_{m_i}, \mathbb{H}(z)) \times \rho \mathbb{E}\left[(1-\kappa) M^{a_i+1}(h_{m_i+1}, z, \mathbb{H}'(z)) + \kappa \max\{V_U^{a_i+1}(h_{m_i+1}), V_{TR}^{a_i+1}(h_{m_i+1})\}\right]}_{\text{future value if successfully climb human capital ladder}}$$

$$+ \Bigg[\underbrace{\left[1 - s(h_{m_i}, \mathbb{H}(z))\right] \times \rho \mathbb{E}\left[(1-\kappa) M^{a_i+1}(h_{m_i}, z, \mathbb{H}'(z)) + \kappa \max\{V_U^{a_i+1}(h_{m_i}), V_{TR}^{a_i+1}(h_{m_i})\}\right]}_{\text{future value if don't successfully climb human capital ladder}} \Bigg].$$

- Match value encompasses spillovers worker i generates to other workers, net of spillovers she receives to avoid double-counting

$$M^{a_i}(h_{m_i}, z, \mathbb{H}(z)) = \max_{l,g} \Bigg[\underbrace{z h_{m_i}(1-l)}_{\text{output value}} - \underbrace{(1-g)l \times q p_e(h_{m_i})}_{\text{pay for external trainers}} + \underbrace{\int_{j \in \mathbb{I}(z), j \neq i} M^{a_j}(h_{m_j}, z, \mathbb{H}(z)) - M^{a_j}(h_{m_j}, z, \mathbb{H}(z) \backslash \{i\}) dj}_{\text{spillovers to other workers in firm}}$$

$$- \underbrace{\int_{j \in \mathbb{I}(z), j \neq i} M^{a_i}(h_{m_i}, z, \mathbb{H}(z)) - M^{a_i}(h_{m_i}, z, \mathbb{H}(z) \backslash \{j\}) dj}_{\text{spillovers from other workers in firm}} + \underbrace{s(h_{m_i}, \mathbb{H}(z)) \times \rho \mathbb{E}\left[(1-\kappa) M^{a_i+1}(h_{m_i+1}, z, \mathbb{H}'(z)) + \kappa \max\{V_U^{a_i+1}(h_{m_i+1}), V_{TR}^{a_i+1}(h_{m_i+1})\}\right]}_{\text{future value if successfully climb human capital ladder}}$$

$$+ \Bigg[\underbrace{\left[1 - s(h_{m_i}, \mathbb{H}(z))\right] \times \rho \mathbb{E}\left[(1-\kappa) M^{a_i+1}(h_{m_i}, z, \mathbb{H}'(z)) + \kappa \max\{V_U^{a_i+1}(h_{m_i}), V_{TR}^{a_i+1}(h_{m_i})\}\right]}_{\text{future value if don't successfully climb human capital ladder}} \Bigg].$$

Learning determination

– Worker of age a and h_{m_i} jointly decides learning with firm z to maximize match value:

$$M^{a_i}(h_{m_i}, z, \mathbb{H}(z)) = \max_{l,g} \left[\underbrace{z h_{m_i}(1-l)}_{\text{output value}} - \underbrace{(1-g)l \times q p_e(h_{m_i})}_{\text{pay for external trainers}} \right]$$

$$\underbrace{\int_{j \in \mathbb{I}(z), j \neq i} \frac{\partial s}{\partial p} \left[p(h_{m_j}, \mathbb{H}(z)) - p(h_{m_j}, \mathbb{H}(z) \backslash \{i\}) \right] \times O^{a_j+1}(h_{m_j}, z, \mathbb{H}'(z)) dj}_{\text{spillovers generated by worker } i \text{ accruing to other workers in firm}}$$

$$+ \underbrace{s(h_{m_i}, \mathbb{H}(z)) \times \rho \mathbb{E} \left[(1-\kappa) M^{a_i+1}(h_{m_i+1}, z, \mathbb{H}'(z)) + \kappa \max\{ V_U^{a_i+1}(h_{m_i+1}), V_{TR}^{a_i+1}(h_{m_i+1}) \} \right]}_{\text{future value if successfully climb human capital ladder}}$$

$$+ \underbrace{[1 - s(h_{m_i}, \mathbb{H}(z))] \times \rho \mathbb{E} \left[(1-\kappa) M^{a_i+1}(h_{m_i}, z, \mathbb{H}'(z)) + \kappa \max\{ V_U^{a_i+1}(h_{m_i}), V_{TR}^{a_i+1}(h_{m_i}) \} \right]}_{\text{future value if don't successfully climb human capital ladder}}.$$

– $O^{a_j+1}(h_{m_j}, z, \mathbb{H}'(z)) = \rho \mathbb{E} \left[(1-\kappa) \Delta M^{a_j+1}(h_{m_j+1}, z, \mathbb{H}'(z)) + \kappa \Delta \max\{ V_U^{a_j+1}(h_{m_j+1}), V_{TR}^{a_j+1}(h_{m_j+1}) \} \right]$

– Also subtract spillovers generated by coworkers accruing to worker i, but these are zero for every worker

Derivation of match value | Unemployment & trainer values | Total & shares of learning time | Back

Wage determination

– Wage each period proportional to current revenue (Cahuc et al. (2006))

$$w^{a_i}(h_{m_i}, z, \mathbb{H}(z)) = r\Bigg[zh_{m_i}(1-l) - (1-g)l \times qp_e(h_{m_i}) + \int_{j\in\mathbb{I}(z), j\neq i} \frac{\partial s}{\partial p}\left[p(h_{m_j}, \mathbb{H}(z)) - p(h_{m_j}, \mathbb{H}(z)\backslash\{i\})\right] \times O^{a_j+1}(h_{m_j}, z, \mathbb{H}'(z))dj\Bigg]$$

– Fraction r is determined upon hiring via Nash Bargaining to maximize match surplus

$$\max_r \left[V^{a_i}(r, h_{m_i}, z, \mathbb{H}(z)) - V_U^{a_i}(h_{m_i})\right]^{\beta} J^{a_i}(r, h_{m_i}, z, \mathbb{H}(z))^{1-\beta}.$$

– β governs the negotiation power of the worker

Worker & Firm Values | Solving for r | Back

Derivation of match value

- We isolate worker j's effect on worker i's match value by comparing the match values worker i obtains when worker j is and isn't in firm z's workforce in the current period, taking all else as given

- Using the envelope theorem, the spillover effect each worker j generates to a worker i is equal to:

$$M^{a_i}(h_{m_i}, z, \mathbb{H}(z)) - M^{a_i}(h_{m_i}, z, \mathbb{H}(z)\backslash\{j\}) \approx$$
$$\frac{\partial s(h_{m_i}, \mathbb{H}(z))}{\partial p(h_{m_i}, \mathbb{H}(z))} \left[p(h_{m_i}, \mathbb{H}(z)) - p(h_{m_i}, \mathbb{H}(z)\backslash\{j\})\right] \times \rho\mathbb{E}\left[(1-\kappa)\Delta M^{a_i+1}(h_{m_i+1}, z, \mathbb{H}'(z)) + \kappa\Delta \max\{V_U^{a_i+1}(h_{m_i+1}), V_{TR}^{a_i+1}(h_{m_i+1})\}\right]$$

- The integral of this expression capturing spillovers to worker i from **all** other workers approx. equal to zero:

$$\approx \frac{D(z)}{D(z)\backslash\{1\}} \int_{j\in\mathbb{I}(z), j\neq i} \left(\mathbf{1}_{\{h_{m_j} > h_{m_i}\}} \frac{1}{D(z)} - \frac{p(h_{m_i}, \mathbb{H}(z))}{D(z)}\right) dj = \frac{D(z)}{D(z)\backslash\{1\}} \left[p(h_{m_i}, \mathbb{H}(z)) - p(h_{m_i}, \mathbb{H}(z))\right] = 0$$

- $D(z)$ is measure of workers in firm z
- Two effects on prob. learn from having worker j: (1) increase in the mass of potential mentors if $h_j > h_i$ (raises prob. by $\frac{1}{D(z)}$ for each j); (2) increase in the workforce (reduces prob. by $\frac{p}{D(z)}$ for each j)
- First effect applies to $D(z)p(h_{m_i}, \mathbb{H}(z))$ mass of workers, so aggregate effect is $p(h_{m_i}, \mathbb{H}(z))$, second effect applies to $D(z)$ mass of workers, so aggregate effect also $p(h_{m_i}, \mathbb{H}(z))$ and cancel out!

Back

Total and shares of learning time

– The total learning time l is given by:

$$l = \left(\frac{\gamma s^E(h_{m_i}, \mathbb{H}(z)), \mathbb{H}(z)) O^{a_i+1}(h_{m_i}, z, \mathbb{H}'(z))}{z h_{m_i} + (1-g) q p_e(h_{m_i})} \right)^{1/(1-\gamma)}.$$

– The relative share of learning time spent on internal learning g satisfies:

$$lq p_e(h_{m_i}) = \left[s^E(h_{m_i}, \mathbb{H}(z))^{\frac{1}{\sigma}} \left(\frac{(A_e(z) p_e(h_{m_i}))^{\frac{\sigma-1}{\sigma}}}{(1-g)^{\frac{1}{\sigma}}} - \frac{(A(z) p(h_{m_i}, \mathbb{H}(z)))^{\frac{\sigma-1}{\sigma}}}{g^{\frac{1}{\sigma}}} \right) \right]$$
$$\times O^{a_i+1}(h_{m_i}, z, \mathbb{H}'(z)) l' = 0.$$

– Where $O^{a_j+1}(h_{m_j}, z, \mathbb{H}'(z)) = \rho \mathbb{E}\left[(1-\kappa) \Delta M^{a_j+1}(h_{m_j+1}, z, \mathbb{H}'(z)) + \kappa \Delta \max\{ V_U^{a_j+1}(h_{m_j+1}), V_{TR}^{a_j+1}(h_{m_j+1}) \} \right]$

– And $s^E(h_{m_i}, \mathbb{H}(z)) = \left[(A(z) p(h_{m_i}, \mathbb{H}(z)) g)^{\frac{\sigma-1}{\sigma}} + (A_e(z) p_e(h_{m_i})(1-g))^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$

Back

Unemployment and Trainer values

– Unemployment value is equivalent to match value in the least productive firm (Bagger et al., 2014):

$$V_U^{a_i}(h_{m_i}) = M^{a_i}(h_{m_i}, z_{min}, \mathbb{H}(z_{min}))$$

– Trainer value:

$$V_{TR}^{a_i}(h_{m_i}) = h_{m_i} q F_e(h_{m_i-1}) + \rho \max\{V_{TR}^{a_i+1}(h_{m_i}), V_U^{a_i+1}(h_{m_i})\}$$

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Solving for r

- According to the FOC, $r^a(h_{m_i}, z)$ satisfies:

$$\frac{V^a(r, h_{m_i}, z) - V_U^a(h_{m_i})}{\beta} = \frac{J^a(r, h_{m_i}, z)}{1-\beta} = M^a(h_{m_i}, z) - V_U^a(h_{m_i}).$$

- We numerically solve for $r^a(h_{m_i}, z)$ by:
  - Solving for the value of employment at any piece rate r
  - Finding the specific piece rate that delivers the value determined by the worker's bargaining outcome

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Worker and Firm Values

– Value for worker of age a and h_{m_i} matched with firm z:

$$V^{a_i}(r, h_{m_i}, z, \mathbb{H}(z)) = r\Bigg[\underbrace{z h_{m_i}(1-l)}_{\text{output value}} - \underbrace{(1-g)l \times q p_e(h_{m_i})}_{\text{pay for external trainers}} + \underbrace{\int_{j \in \mathbb{I}(z), j \neq i} \frac{\partial s}{\partial p}\left[p(h_{m_j}, \mathbb{H}(z)) - p(h_{m_j}, \mathbb{H}(z)\backslash\{i\})\right] O^{a_j+1}(h_{m_j}, z, \mathbb{H}'(z)) dj}_{\text{spillover effects to other workers in firm}}$$

$$+ \underbrace{s(h_{m_i}, \mathbb{H}(z)) \times \rho \mathbb{E}\left[(1-\kappa)V^{a_i+1}(r, h_{m_i+1}, z, \mathbb{H}'(z)) + \kappa \max\{V_U^{a_i+1}(h_{m_i+1}), V_{TR}^{a_i+1}(h_{m_i+1})\}\right]}_{\text{future value if successfully climb human capital ladder}}$$

$$+ \underbrace{\left[1 - s(h_{m_i}, \mathbb{H}(z))\right] \times \rho \mathbb{E}\left[(1-\kappa)V^{a_i+1}(r, h_{m_i}, z, \mathbb{H}'(z)) + \kappa \max\{V_U^{a_i+1}(h_{m_i}), V_{TR}^{a_i+1}(h_{m_i})\}\right]}_{\text{future value if don't successfully climb human capital ladder}}$$

– Value from that match for firm z:

$$J^{a_i}(r, h_{m_i}, z, \mathbb{H}(z)) = (1-r)\Bigg[\underbrace{z h_{m_i}(1-l)}_{\text{output value}} - \underbrace{(1-g)l \times q p_e(h_{m_i})}_{\text{pay for external trainers}} \underbrace{\int_{j \in \mathbb{I}(z), j \neq i} \frac{\partial s}{\partial p}\left[p(h_{m_j}, \mathbb{H}(z)) - p(h_{m_j}, \mathbb{H}(z)\backslash\{i\})\right] O^{a_j+1}(h_{m_j}, z, \mathbb{H}'(z)) dj}_{\text{spillover effects to other workers in firm}}$$

$$+ \underbrace{s(h_{m_i}, \mathbb{H}(z)) \times \rho \mathbb{E}(1-\kappa) J^{a_i+1}(r, h_{m_i+1}, z, \mathbb{H}'(z))}_{\text{future value if successfully climb human capital ladder}} + \underbrace{\left[1 - s(h_{m_i}, \mathbb{H}(z))\right] \times \rho \mathbb{E}(1-\kappa) J^{a_i+1}(r, h_{m_i}, z, \mathbb{H}'(z))}_{\text{future value if don't succesfully climb human capital ladder}}.$$

Back

Vacancy determination

– Each firm chooses $v(z)$ to maximize its share of the surplus from hiring workers:

$$\max_{v(z)} \frac{v(z)}{V} \sum_{m=1}^{M} \sum_{a=1}^{J} \lambda_U (1-\beta) \left[M^a(h_m, z, \mathbb{H}(z)) - V_U^a(h_m) \right] D_U^a(h_m) - c_v \frac{v(z)^{1+\gamma_v}}{1+\gamma_v}$$

– $D_U^a(h_m)$ is measure of unemployed of age a and h_m

– λ_U is meeting rate for unemployed workers: $\lambda_U = c_M(\frac{V}{U})^{\phi}$

– The first-order condition yields

$$c_v v(z)^{\gamma_v} = \sum_{m=1}^{M} \sum_{a=1}^{J} \frac{\lambda_U (1-\beta)}{V} \left[M^a(h_m, z, \mathbb{H}(z)) - V_U^a(h_m) \right] D_U^a(h_m)$$

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Externally calibrated parameters

Label	Description	Value	Source
ρ	Discount rate	0.99	Annual interest rate of 0.04
J	Working life	160	Working life of 40 years
γ_h	Step size of human capital ladder	0.05	Authors' choice
h_1	Lower bound of human capital ladder	1	Normalization
ϕ	Elasticity of matches to vacancies	0.3	Shimer (2005)
β	Workers' bargaining power	0.5	Estimates in literature
γ_v	Curvature of vacancy cost	1	Dix-Carneiro et al. (2019)

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Targeted moments

Description	Model	Data
1. Unemployment rate	0.06	0.06
2. Labor market tightness (#vacancies/#unemployed)	0.53	0.55
3. Shape parameter of firm employment distribution[1]	1.26	1.10
4. Share of workers that remain employed in next quarter	0.97	0.94
5. Average wage growth from HC (per quarter) within 0–10 years of experience	0.0094	0.0078
6. Average wage growth from HC (per quarter) within 0–25 years of experience	0.0034	0.0040
7. Average wage growth from HC (per quarter) within 0–40 years of experience	0.0021	0.0023
8. Share of total time spent on internal learning	0.029	0.033
9. Share of total time spent on external learning	0.014	0.014
10. Ratio of total learning time in 100+ worker firms to 50–99 worker firms	1.17	1.13
11. Ratio of all to new workers' average time spent on external learning	1.52	1.51
12. Ratio of old to all workers' average learning time	0.46	0.51

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Internally calibrated parameters

- Efficiency of learning internally & externally parametrized as: $A(z) = \bar{A}z^{\alpha}$; $A_e(z) = \bar{A}_e z^{\alpha}$
- $\alpha > 0$ captures potentially higher learning efficiency in more productive firms

Label	Description	Value
$\bar{A}$	Constant in efficiency of internal learning	0.47
$\bar{A}_e$	Constant in efficiency of external learning	0.25
α	Elasticity of learning efficiency to firm productivity	0.66
σ	Elasticity of substitution between internal/external learning	3.83
ϵ	Exogenous human capital gain	0.03
δ_ϵ	Decline of exogenous human capital gain with regard to human capital	0.06
γ	Degree of diminishing returns in learning	0.46
δ_h	Depreciation rate of human capital	0.02
c_m	Constant in matching function	0.45
c_v	Constant in vacancy cost function	0.31
ζ	Shape parameter of firm productivity distribution	4.65
κ	Exogenous separation rate	0.03

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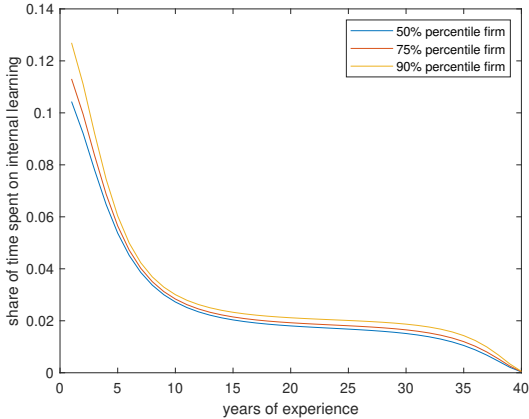
Survey of Employer-Provided Training in 1995 (US-SEPT)

- Enterprise-level survey focusing on firms with 50+ workers across industries & states
- External & internal learning can be roughly matched to formal & informal training
  - Formal training: Structured training that is planned in advance (e.g classes/seminars)
  - Informal training: Unstructured & adaptable training (e.g learn from coworker/supervisor)

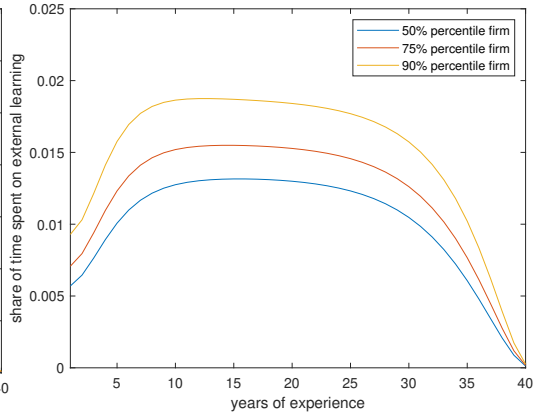
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More productive firms offer more learning of both sources

(a) Internal learning

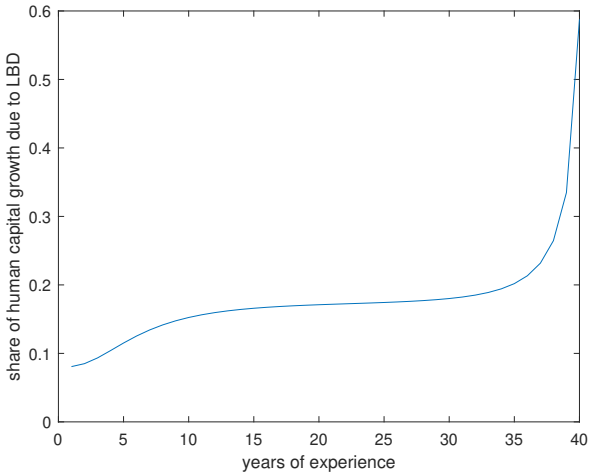


(b) External learning



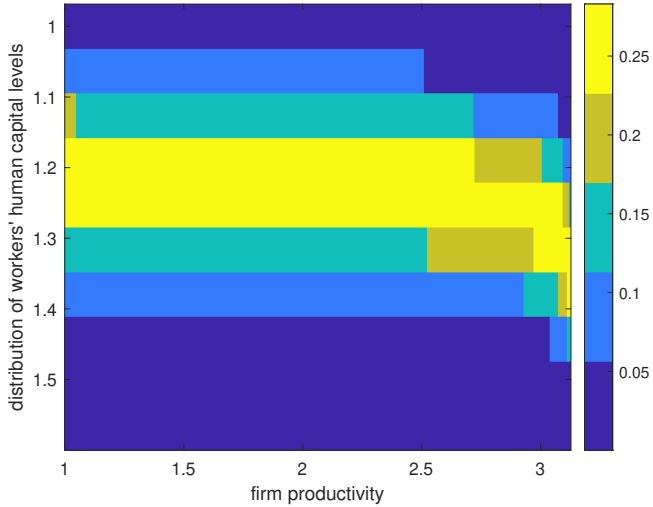
Positive assortative matching | Distribution of trainer v. worker human capital | Back

Share of human capital growth due to learning-by-doing



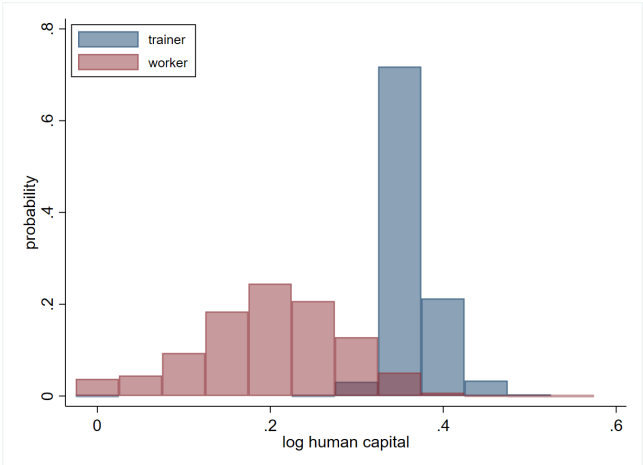
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Positive sorting between workers and firms



Back

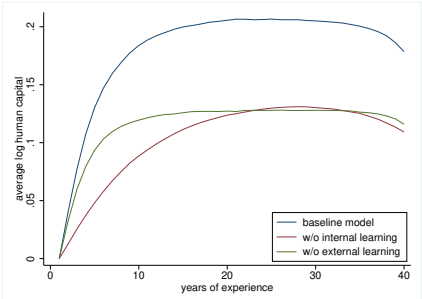
Distribution of trainer v. worker human capital



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Role of each source: shut down external and internal learning

	Share of time learning		
	External	**Internal**	**Avg** h
Calibrated economy	1.42%	2.91%	1.22
W/o **external learning**	0	3.02%	1.14
W/o **internal learning**	1.46%	0	1.12
W/o **both sources of learning**	0	0	1.04
W/o **any form of learning**	0	0	1



⇒ Avg human capital falls 6.6% w/o **external**, 8.2% w/o **internal**

⇒ **Internal learning** 1.24 times as important

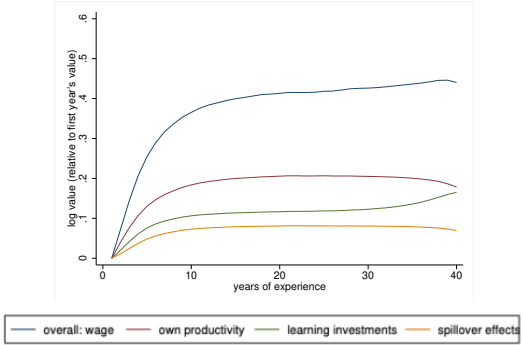
⇒ But **internal** particularly important during youth; **external** more critical later

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Wage decomposition

Human capital affects wages via: own productivity; learning costs; coworker spillovers >

Spillovers + learning costs explain 47% of lifecycle wage growth from HC



- Spillover & learning costs are also key to explain lifecycle wage dispersion >
- Both sources matter: **internal** lets knowledgeable workers be paid for spillovers; **external** builds the skills behind those spillovers

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Wage decomposition into different components

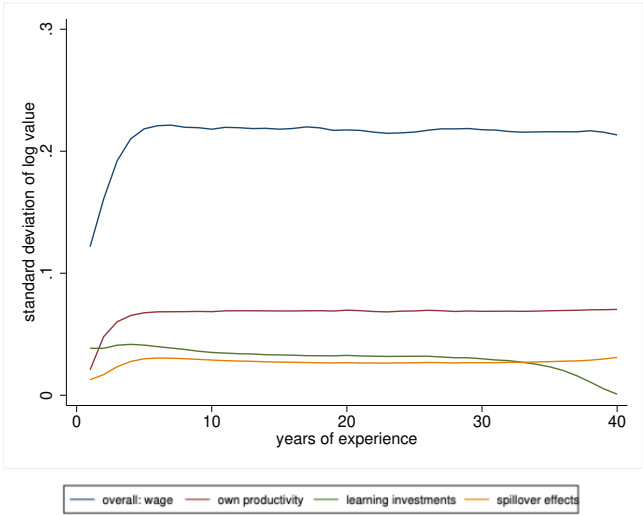
$$\log w^{a_i}(h_{m_i}, z, \mathbb{H}(z)) = \underbrace{\log r}_{\text{piece rate}} + \underbrace{\log z}_{\text{firm productivity}} + \underbrace{\log h_{m_i}}_{\text{worker's own productivity}}$$

$$+ \underbrace{\log\left(\frac{zh_{m_i} + X^{a_i}(h_{m_i}, z, \mathbb{H}(z))}{zh_{m_i}}\right)}_{\text{spillover effects to other workers in the firm}} + \underbrace{\log\left(\frac{zh_{m_i}(1-l) - (1-g)lqp_e(h_{m_i}) + X^{a_i}(h_{m_i}, z, \mathbb{H}(z}{zh_{m_i} + X^{a_i}(h_{m_i}, z, \mathbb{H}(z))}\right)}_{\text{learning costs}}$$

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Non own productivity effects also key to explain lifecycle wage dispersion

– Decompose wage into same components as before: own productivity, spillovers, learning costs



Additional counterfactual results

- Role of each source of learning in wage growth >
  - Without internal learning, wage growth is primarily driven by changes in workers' productivity

- Role of each source of learning in wage dispersion >
  - Lifecycle increase in human capital dispersion largely driven by external learning
  - But! Lifecycle increase in wage dispersion largely driven by spillover effects

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Coworker tutoring tasks are common & require high skill

- Model predicts that tutoring key for wage growth, particularly high-skill workers
- To test: **Use US O*NET data on tasks & skills needed in 900 occupations**
  - Count how many non-teaching occupations have tutoring tasks (thru relevant activities/skill, importance rated 1–7 by analysts)
  - Examine experience and education requirements of tutoring-heavy occupations (thru job zone measuring education, experience and training required, rated 1–5 by analysts)

Table: Importance of tutoring activities/skills in non-teaching occupations in the US (information for non-teaching occupations with 3.5+ score in each activity/skill)

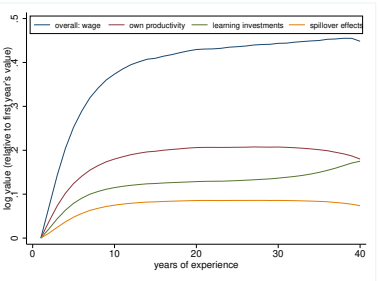
	# Occs	Share occs	Avg score	Avg job zone
Importance of guiding, directing, and motivating subords. activity	57	0.067	4.24	3.97
Importance of coaching and developing others activity	27	0.032	4.22	4.15
Importance of training and teaching others activity	46	0.054	4.12	4.22
Importance of instructing skill	99	0.12	4.13	3.88

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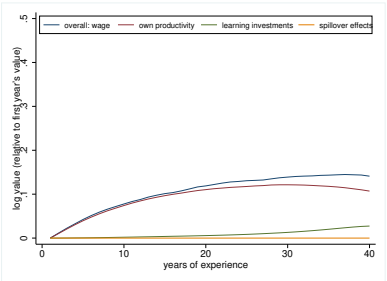
Role of each source of learning in wage growth

– Decompose wage into same components as before: own productivity, spillovers, learning costs

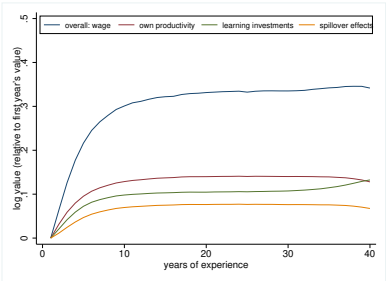
(a) Baseline Model



(b) Without Internal learning



(c) Without External learning



– Without external learning, lower overall wage growth, but patterns similar to baseline

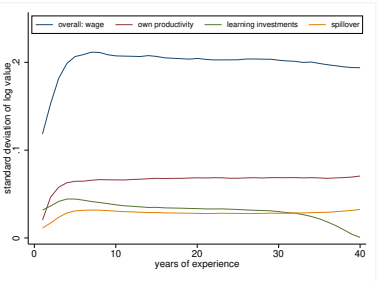
– Without internal learning, wage growth is mostly driven by workers' own-productivity

Back

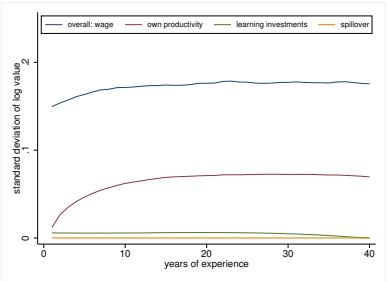
Role of each source of learning in wage dispersion

– Decompose wage into same components as before: own productivity, spillovers, learning costs

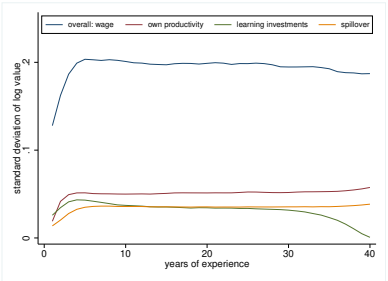
(a) Baseline Model



(b) Without Internal learning



(c) Without External learning



– Lifecycle increase in human capital dispersion largely driven by external learning

– But! Lifecycle increase in wage dispersion largely driven by spillover effects

Counterfactual human capital distributions Back

Evidence on testable predictions

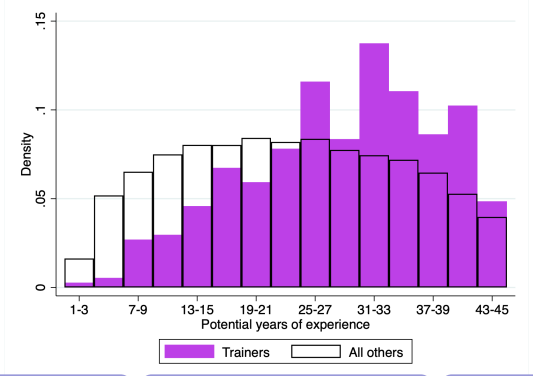
1. Human capital distribution of trainers is skewed left relative to prod. workers > ✓
2. Portion of workers who learn-by-doing rises with human capital > ✓
3. Task complexity ranking: **internal learners** $<$ **external learners** > ✓

Back

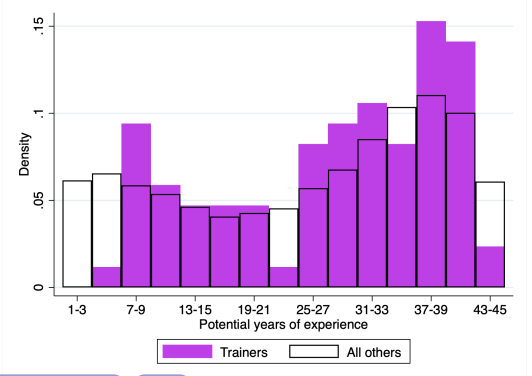
1. Human capital distribution of trainers is skewed left

- Model predicts: Trainers have higher human capital than production workers
- To test: Plot & compare histograms of trainers v. production workers by experience
  - **Trainer**: Occupations of training or instruction outside of school/university
  - **Production worker**: Not trainer

(a) Germany



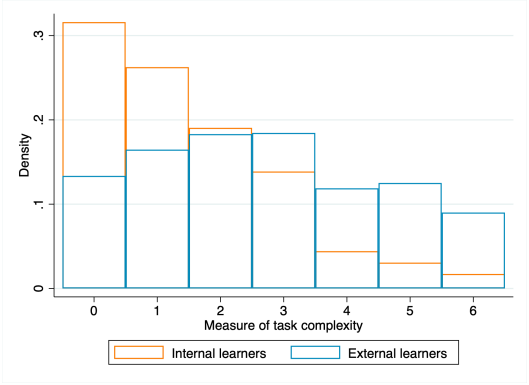
(b) United States



Quantile regression | Alternate production worker definition | Trainer v. external/internal learner | Back

2. Task complexity ranking across internal/external learners

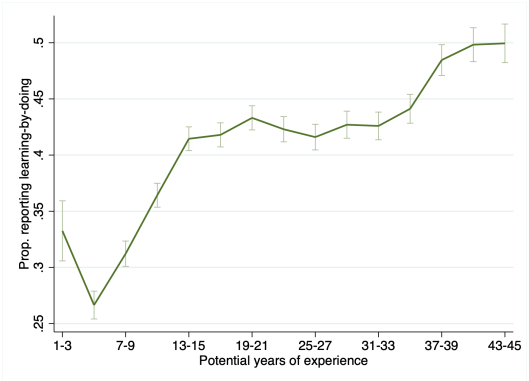
- Model predicts: Human capital of internal learners $<$ human capital external learners
- To test: Plot & compare histograms of task complexity for internal v. external learners (only for Germany)
  - **Measure of task complexity**: How many "complex" skills workers' use in their jobs (Math & Stats; Foreign Language; Computing; Accounting; Marketing; Management)



Quantile regression Tool use Back

3. Portion of workers who learn-by-doing rises with human capital

- Model predicts: Opp. cost of internal/external learning rises with h (LBD free)
- To test: Construct a measure of "learning-by-doing" and plot against potential experience
  - **Learning-by-doing**: Learned how to do their job via the job itself (only for Germany)



Notes: 95% confidence intervals plotted.

Table Back

Quantile regression trainer v. production worker

Germany

	Potential years of experience					
	25th percentile		50th percentile		75th percentile	
Trainer	4***	4***	3	3***	3**	2.5*
	(1.254)	(1.463)	(2.005)	(1.015)	(1.254)	(1.467)
Constant	14***	3***	24***	14***	33***	25***
	(0.0529)	(0.354)	(0.0423)	(0.266)	(0.0529)	(0.422)
Observations	173,639	165,265	173,639	165,265	173,639	165,265
Year FE		Y		Y		Y
Demographic controls		Y		Y		Y
Worker type FE		Y		Y		Y
Firm size FE		Y		Y		Y

United States

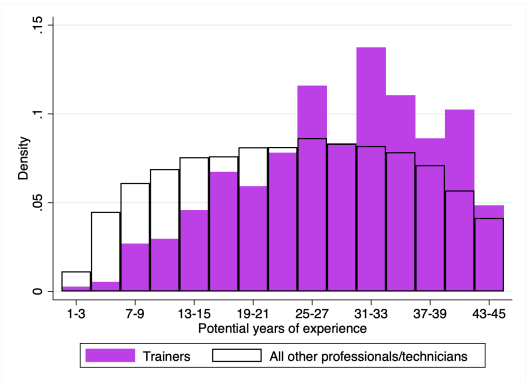
	Potential years of experience					
	25th percentile		50th percentile		75th percentile	
Trainer	4	4	-1	4**	1	3
	(7.557)	(6.560)	(6.044)	(1.593)	(3.782)	(6.761)
Constant	10***	11***	20***	24***	31***	35***
	(0.186)	(0.375)	(0.149)	(0.496)	(0.186)	(0.410)
Observations	29,217	29,217	29,217	29,217	29,217	29,217
Demographic controls		Y		Y		Y
Worker type FE		Y		Y		Y

Back

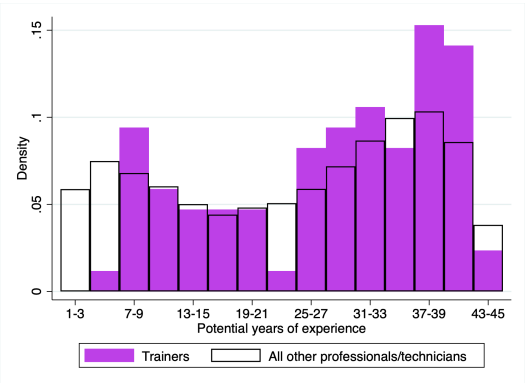
Histograms trainer v. production worker (alt. definition)

- **Trainer**: Occupations of training or instruction outside of school/university
- **Production worker**: Not trainer + professional or technical occupation

(a) Germany



(b) United States

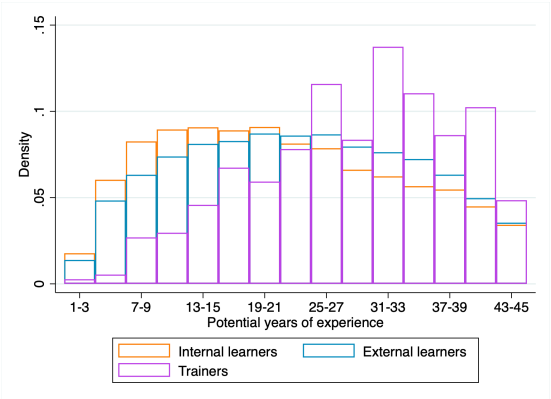


Back

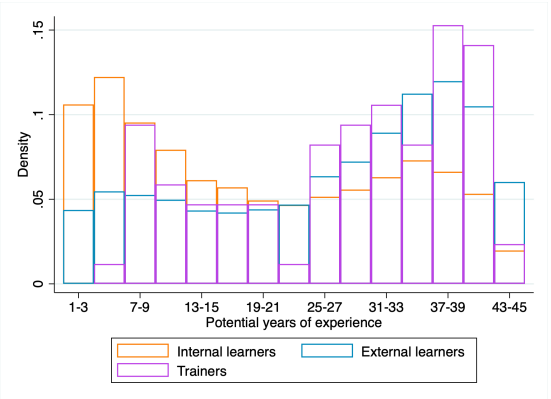
Histograms trainer v. external learner & internal learner

- **Trainer**: Occupations of training or instruction outside of school/university
- **External/internal learner**: Reports external/internal learning (as before)

(a) Germany



(b) US



Back

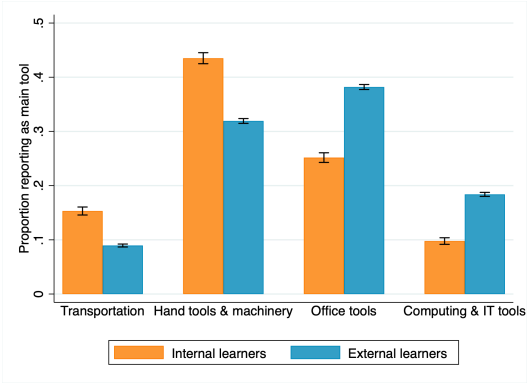
Quantile regression of task complexity

	Task complexity	
	50th percentile	
External learner	2***	0.584***
	(0.0991)	(0.222)
Constant	1***	3.827***
	(0.0940)	(0.840)
Observations	84,315	29,322
Year FE		Y
Demographic controls		Y
Age FE		Y
Worker type FE		Y
Industry FE		Y
Occupation FE		Y
Firm size FE		Y
Wage controls		Y

Back

2. Task complexity ranking across internal/external learners

- Additional evidence of task complexity differences: compare tool use (only for Germany)
- **Blue-collar tools**: transportation (trucks, forklifts), hand tools (hammers, hair dryers)
- **White-collar tools**: office equipment (pens, phones, calculators), computers/IT



Regression Back

Regression of tool use

	White-collar tools		
External learner	0.209***	0.0419***	0.0433***
	(0.00508)	(0.00496)	(0.00845)
Constant	0.373***	0.363***	0.262***
	(0.00458)	(0.0183)	(0.0283)
Observations	87,047	53,163	29,162
R-squared	0.026	0.617	0.623
Year FE		Y	Y
Demographic controls		Y	Y
Age FE		Y	Y
Worker type FE		Y	Y
Industry FE		Y	Y
Occupation FE		Y	Y
Firm size FE		Y	Y
Wage controls			Y

Back

Correlation between learning-by-doing and experience in Germany

	Learning-by-doing		
Potential years of experience	0.0091***	0.0084***	0.0091***
	(0.0007)	(0.0009)	(0.0014)
Potential years of experience^2	-9.87e-05***	-9.18e-05***	-9.82e-05***
	(1.54e-05)	(1.93e-05)	(2.99e-05)
	(0.00772)	(0.0216)	(0.0303)
Observations	90,536	51,455	21,378
R-squared	0.011	0.123	0.081
Year FE		Y	Y
Demographic controls		Y	Y
Worker type FE		Y	Y
Industry FE		Y	Y
Occupation FE		Y	Y
Firm size FE		Y	Y
Wage controls			Y

Back

Additional exercises and robustness

Additional exercise: 50% subsidy to external learning (median across US states) >

- Inefficiency: Learning choice does not internalize gains to future employers & coworkers

⇒ Ignoring **internal learning** overstates subsidy's benefits for young workers but understates them for old

Robustness

- Incorporate on-the-job search
- Incorporate time costs of mentoring for colleagues workers learn from
- Incorporate heterogeneity in initial human capital matching schooling distribution
- Incorporate unemployment benefits
- Incorporate fixed learning cost to consider extensive margin of learning
- Incorporate endogenous quitting to become a trainer
- Alternate values of workers' bargaining power (β), and elasticity of substitution between learning modes (σ)

⇒ Results are remarkably robust across all extensions!

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Subsidies to learning

- Learning investments maximize match value
- But, choice doesn't internalize gains to future employers & coworkers after workers leave
- Scope for policy to correct inefficiencies & spawn human capital accumulation & growth
- Consider: Government-sponsored subsidies to **external learning**
  - 50% subsidy, which is median among US states
  - Financed by lump-sum taxes

Subsidies to all learning costs: 31% subsidy rate ⇒ 2.1% gain in GDP

	Benchmark	Impact of training subsidies (rel. to baseline)
Avg human capital	1.22 38.81%	7.02%
Δ log wage, 0–5 yrs of exp	0.255	42.59%
Δ log wage, 5–25 yrs of exp	0.163	76.23%

⇒ Young workers' gain moderated by **internal learning** as they prefer that for learning

⇒ Old workers' gain amplified by **internal learning** as they can "spillover" subsidy effect

⇒ Considering both learning sources is key!

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	Workers' share of time spent on learning		
	External learning	Internal learning	Avg Human Capital
Panel A: Incorporating on-the-job search			
Calibrated economy	1.41%	3.19%	1.26
W/o internal learning	1.46%	0	1.13
W/o external learning	0	3.72%	1.16
Panel B: Incorporating time costs for internal trainers			
Calibrated economy	1.37%	3.01%	1.22
W/o internal learning	1.42%	0	1.11
W/o external learning	0	2.97%	1.13
Panel C: Incorporating heterogeneity in initial human capital			
Calibrated economy	1.50%	3.23%	1.38
W/o internal learning	1.79%	0	1.23
W/o external learning	0	3.45%	1.26
Panel D: Incorporating unemployment benefits			
Calibrated economy	1.41%	2.51%	1.25
W/o internal learning	1.50%	0	1.15
W/o external learning	0	3.39%	1.17
Panel E: Incorporating a fixed learning cost to consider extensive margin of learning			
Calibrated economy	1.25%	2.78%	1.22
W/o internal learning	1.26%	0	1.11
W/o external learning	0	2.61%	1.13
Panel F: Voluntary quits into training sector			
Calibrated economy	1.39%	2.83%	1.23
W/o internal learning	1.45%	0	1.12
W/o external learning	0	3.05%	1.15
Panel G: Setting workers' bargaining power $\beta = 0.3$			
Calibrated economy	1.35%	2.84%	1.22
W/o internal learning	1.41%	0	1.12
W/o external learning	0	2.96%	1.14
Panel H: Setting workers' bargaining power $\beta = 0.7$			
Calibrated economy	1.43%	2.90%	1.23
W/o internal learning	1.54%	0	1.12
W/o external learning	0	3.10%	1.14
Panel I: Setting elasticity of substitution between learning modes $\sigma = 5$			
Calibrated economy	1.61%	2.76%	1.22
W/o internal learning	2.04%	0	1.14
W/o external learning	0	2.90%	1.14

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	Benchmark	Impact of shocks (rel. to baseline)		
		Shift to remote work 20% remote	Shift to remote work 100% remote	50% subsidy for external learning
Panel A: Incorporating on-the-job search				
Average human capital	1.26	-0.31%	-3.73%	8.66%
Δ log wage, 0–5 yrs of exp	0.455	-1.73%	-18.18%	37.06%
Average human capital	1.22	-0.41%	-3.05%	7.17%
Δ log wage, 0–5 yrs of exp	0.256	-2.78%	-25.98%	43.00%
Panel C: Incorporating heterogeneity in initial human capital				
Average human capital	1.38	-1.12%	-3.38%	7.55%
Δ log wage, 0–5 yrs of exp	0.212	-10.11%	-33.06%	55.23%
Panel D: Incorporating unemployment benefits				
Average human capital	1.25	-0.55%	-3.11%	9.59%
Δ log wage, 0–5 yrs of exp	0.265	-5.91%	-25.67%	45.70%
Panel E: Incorporating a fixed learning cost to consider extensive margin of learning				
Average human capital	1.22	-0.37%	-2.84%	3.39%
Δ log wage, 0–5 yrs of exp	0.254	-3.96%	-23.61%	22.08%
Panel F: Voluntary quits into training sector				
Average human capital	1.23	-0.39%	-3.09%	3.94%
Δ log wage, 0–5 yrs of exp	0.264	-3.54%	-26.85%	28.82%
Panel G: Setting workers' bargaining power $\beta = 0.3$				
Average human capital	1.22	-0.37%	-2.71%	6.49%
Δ log wage, 0–5 yrs of exp	0.249	-3.50%	-25.67%	36.96%
Panel H: Setting workers' bargaining power $\beta = 0.7$				
Average human capital	1.23	-0.36%	-3.04%	6.72%
Δ log wage, 0–5 yrs of exp	0.269	-4.52%	-26.55%	39.75%
Panel I: Setting elasticity of substitution between learning modes $\sigma = 5$				
Average human capital	1.22	-0.35%	-2.07%	10.15%
Δ log wage, 0–5 yrs of exp	0.254	-3.79%	-27.78%	55.10%

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Evidence of shift from internal to external learning due to remote work in SWAA

SWAA Data: Custom worker learning module fielded in Dec 2023 within the *Survey of Working Arrangements and Attitudes (SWAA)* (Barrero et al., 2021)

- **Internal learning**: Reported spending time in the past month being mentored, discussing their performance with a supervisor, or attending training sessions led by colleagues or managers.
- **External learning**: Reported spending time in the past month attending training sessions led by persons outside their workplace or engaging in self-learning using external materials
- **Key feature:** Also asks how internal/external learning changed *relative to 2019*
- Sample: Individuals who are currently working, have 1–45 years of potential experience, passed all attention checks, do not work fully remotely
- **Specification:** Regress changes in internal/external learning since 2019 on share of days worked remotely last week

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Evidence of shift from internal to external learning due to remote work in PIAAC

PIAAC Data: Survey on learning & skills of workers 16–65 in OECD, conducted in 2011–2017 (pre-Covid) & 2022–2023 (pre-Covid)

- **Internal learning**: Reports learning skills from coworkers often in current work
- **Key feature:** Has large sample + rich occupation info so can use IV with *occupation-based telework suitability* (Dingel and Neiman, 2020)
- Sample: Individuals who are currently working, and have 1–45 years of realized & potential experience
- **Specification:** Regress internal/external learning in 2011–2017 (pre-Covid) & 2022–2023 (post-Covid) on index of ICT use at work (proxy for remote work exposure) using DiD and IV-DiD

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