Advances in Digital Technologies in Europe and their Local Labor Market Effects

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Motivation

- Rapid technological change and increasing capabilities in AI and robotics over the last 30 years
- Impacts on the labor market ambiguous
- Objectives:
  - Create new measures for AI and robotics using patent data
  - Use these measures to estimate labor market effects in Germany

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Research Questions:

How did patenting in AI and robotics develop between 1990 and 2018?

What are the employment and wage effects of these advances in technology?

Previous Literature

Literature on measuring technological change:

- Patents as proxies for TC (Griliches 1990, Jaffe 1993, Bessen & Hunt 2007)
- New patent-based approaches (Mann & Püttmann 2018, Dechezlepretre 2019, Webb 2020) $\rightarrow$ **text instead of metadata**

Previous Literature

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Literature on LM effects of digitalisation:

- Early papers on computerization and ICT (Autor et al. 1998, Autor et al. 2003) → focus on SBTC → **routine-replacing effects**
- Impact of robots in manufacturing (Graetz & Michaels 2018, Acemoglu & Restrepo 2020, Dauth et al. 2021) → **ambiguous effects**
- Little on AI, mainly on occupational level and for the US (Brynjolfson 2018, Felten 2019, Webb 2020, Acemoglu et.al 2022)

Our contributions

- **New patent-based measures of AI and robotics**
  - Using **NLP on patent text**
  - Mapping to detailed 3-digit industry of use
  - Variation over time: yearly data from 1990 to 2018

Our contributions

- **New patent-based measures of AI and robotics**
  - Using **NLP on patent text**
  - Mapping to detailed 3-digit industry of use
  - Variation over time: yearly data from 1990 to 2018
- **Estimating employment and wage effects**
  - Using high-quality administrative data from Germany
  - Cover both services and manufacturing + 2 technologies
    $\rightarrow$ **measure broad impact**
  - Estimate effects on plant and local labor market level

Identifying AI and robotics patents

- **Data**: European Patent Office, 1990 to 2018
- Keyword-based classification using NLP
    - Use patent text (title & abstract) as input
    - NLP steps: remove stopwords & special characters, stemming, tokenization
    - Sample keywords: machin[e] learn[ing], neural network, bayes[ian] learn[ing], robot

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(19) Europäisches Patentamt
European Patent Office
Office européen des brevets

(11) **EP 2 259 215 A1**

(12) **EUROPEAN PATENT APPLICATION**

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G06N 7/00 (2006.01) ***G06N 3/04*** (2006.01)

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(22) Date of filing: **09.11.2009**

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Designated Extension States:
AL BA RS

(30) Priority: **04.06.2009 EP 09161922**

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63500 Seligenstadt (DE)

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Mitscherlich & Partner
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Remarks:
Amended claims in accordance with Rule 137(2) EPC.

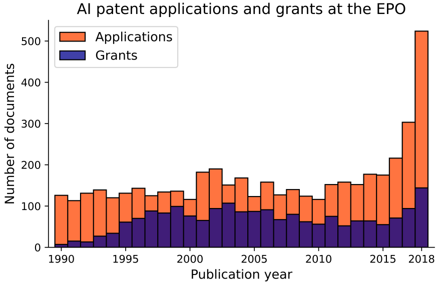
(54) **Method and structure for a neural associative memory based on optimal Bayesian learning**

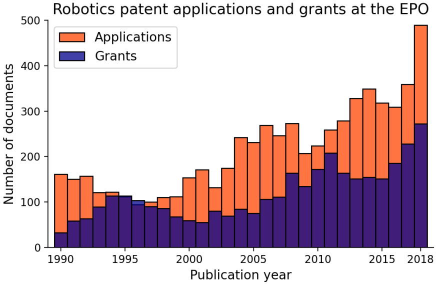
(57) This invention is in the field of machine learning and neural associative memory. In particular the invention discloses a neural associative memory structure for storing and maintaining associations between memory address patterns and memory content patterns using a neural network, as well as methods for storing and retrieving such associations. Bayesian learning is applied to achieve non-linear learning.

$$(u^1,v^1),\ (u^2,v^2),\ \ldots,\ (u^M,v^M) \longrightarrow \boxed{\text{AM}}$$

Fig. 1a

- Development of AI and robotics patents between 1990 and 2018:





Mapping patents to industries

- Apply **probabilistic mapping** (Lybbert & Zolas 2014, 2019)
- From patent CPC codes to ISIC industry codes

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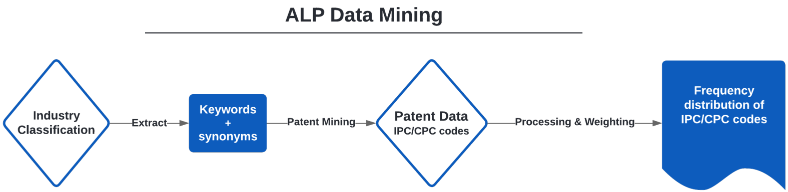

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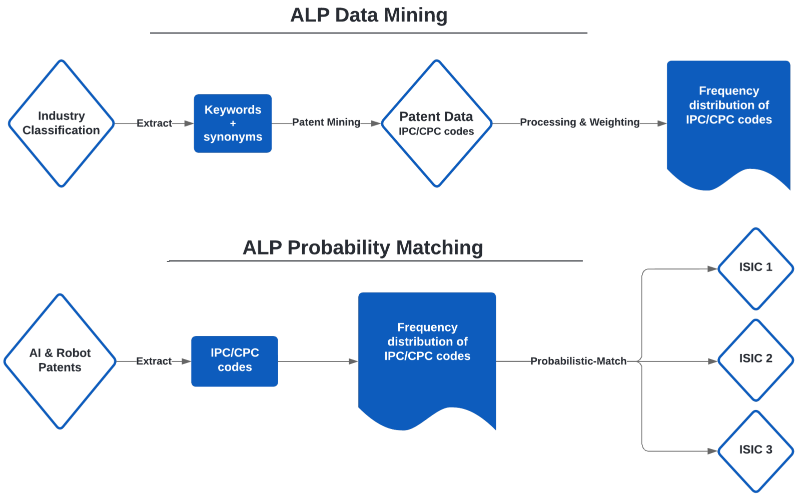
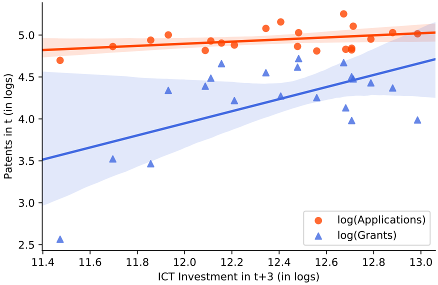
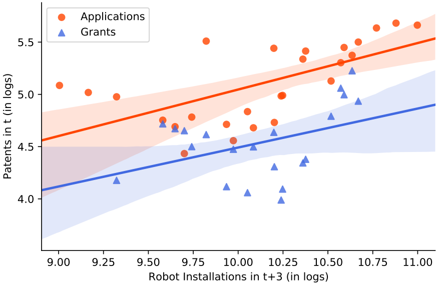


Validation: Comparison to previous measures

- AI: compare to ICT investment (EU KLEMS)
- Robotics: compare to robot installations (IFR)





Patent Exposure Measure

Industry-level patent measure:

$$Pat^{c}_{i,t} = \sum_{s \in t} Log(1 + Pat^{c}_{i,s})$$

with t subperiods 1990-1998, 1990-2005, 1990-2011, 1990-2018

- Patents as cumulative process of knowledge creation: Sum of patents until end of period
- Log transformation due to large differences in number of patents
- Defined for 4 subperiods

Labor Market Data

- IAB Establishment History Panel (BHP) for 1990-2018
- **Main outcome variables**: (log) number of employees, (log) median wages
- At plant level or aggregated to districts
- **Control variables**: workforce characteristics (skill, age, gender), industry employment shares, net exports, ICT investment, initial firm employment

Estimation Strategy

Plant level:

$Y_{fit} = \beta_c Pat^c_{i,t} + \gamma initialemp_{ft} + \theta_f + \delta_t + \epsilon_{fit}$, c= AI or robots

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$Y_{fit} = \beta_c Pat^c_{i,t} + \gamma initialemp_{ft} + \theta_f + \delta_t + \epsilon_{fit}$, c= AI or robots

District level:

- **Shift-Share design**
- Evolution of patents in industry → **"shift"**
- Industry structure of LLM in **base year (1993)** → **"shares"**
- Exposure at the district level: $Exposure^c_{r,t} = \sum_{i=1}^{I} \left(\frac{Emp^{1993}_{i,r}}{Emp^{1993}_r} * Pat^c_{i,t} \right)$

$Y_{r,t} = \beta Exposure_{r,t} + \delta' X_{rt} + \gamma_1 Trade_{r,t} + \gamma_2 ICT_{r,t} + \theta_t + \alpha_r + \epsilon_{r,t}$

Results 1: Plant Level Employment Effects

	overall	low-skill	medium-skill	high-skill
Employment	(1)	(2)	(3)	(4)
AI Exposure	-0.003***	**-0.007*** **	**-0.002*** **	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Robot Exposure	-0.001***	**-0.003*** **	0.000	**0.001** **
	(0.000)	(0.001)	(0.000)	(0.000)
Firm FE	✓	✓	✓	✓
Period FE	✓	✓	✓	✓
Initial Employment	✓	✓	✓	✓
Observations	3349921	3349921	3349921	3349921

AI Exposure $\uparrow$: overall emp. $\downarrow$ 1.1%, low skill emp. $\downarrow$ 2.7%

Robot Exposure $\uparrow$: overall emp. $\downarrow$ 0.7%., low skill emp. $\downarrow$ 2%

Results 2: District Employment Effects

Employment changes	overall (1)	low-skill (2)	medium-skill (3)	high-skill (4)
AI Exposure	-0.013***	-0.0174***	-0.0132***	-0.0065
	(0.003)	(0.0055)	(0.0027)	(0.0056)
Robot Exposure	-0.006***	**-0.0112*** **	-0.0057***	-0.0052**
	(0.001)	(0.0023)	(0.0013)	(0.0023)
District FE	✓	✓	✓	✓
Period FE	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Industry shares	✓	✓	✓	✓
Net exports	✓	✓	✓	✓
ICT investment	✓	✓	✓	✓
Observations	1604	1604	1604	1604

AI Exposure ↑: overall emp. ↓ 2.3%, low skill emp. ↓ 3%

Robot Exposure ↑: overall emp. ↓ 2.5%., low skill emp. ↓ 4.6%

Results 3: District Employment Manufacturing vs. Services

Employment changes	Manufacturing				Non-Manufacturing			
	overall (1)	low (2)	medium (3)	high-skill (4)	overall (5)	low (6)	medium (7)	high-skill (8)
AI Exposure	**-0.0355***** (0.0105)	-0.0345*** (0.0133)	-0.0335*** (0.0095)	-0.0440** (0.0184)	**-0.0018** (0.0029)	-0.0136** (0.0053)	-0.0032 (0.0027)	**0.0093** (0.0059)
Robot Exposure	**-0.0160***** (0.0052)	-0.0204*** (0.0056)	-0.0145*** (0.0046)	-0.0222** (0.0094)	**-0.0025*** (0.0014)	-0.0088*** (0.0023)	-0.0027** (0.0013)	**0.0012** (0.0027)
District FE	✓	✓	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓	✓	✓
Industry shares	✓	✓	✓	✓	✓	✓	✓	✓
Net exports	✓	✓	✓	✓	✓	✓	✓	✓
ICT investment	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1604	1604	1604	1604	1604	1604	1604	1604

Negative effects driven by manufacturing employment:

AI Exposure ↑: manufacturing emp. ↓ 6.3%

Robot Exposure ↑: manufacturing emp. ↓ 6.6%.

Conclusion

- **Increasing patenting activity** $\rightarrow$ high relevance of AI & robotics
  - Patents as important proxy for TC
- **Plant level:** Negative employment effects concentrated on low-skill workers.
- **District level:** Strong automation component for both technologies but varying by sector and skill level.
  - AI effects concentrated on low- and medium-skill workers.
  - Robot effects negative for all skill groups.
  - **Strongest negative effects in Manufacturing sector.**
- Wage effects seem to be small; slightly positive at firm level.

Thank you!

Feel free to reach out:

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Appendix

Robustness Check: Excluding German Patents

	Manufacturing				Non-Manufacturing			
	overall	low-skill	med-skill	high-skill	overall	low-skill	med-skill	high-skill
Employment changes	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔAI Exposure	**-0.0221***	0.000688	**-0.0226****	-0.0232	0.00417	0.00187	0.00162	0.0165
	(0.0119)	(0.0171)	(0.0111)	(0.0219)	(0.00496)	(0.00882)	(0.00424)	(0.0108)
ΔRobot Exposure	-0.00951	**-0.0204*****	-0.00767	-0.0162	**-0.00389***	**-0.00950*****	**-0.00338***	-0.00414
	(0.00639)	(0.00698)	(0.00574)	(0.0119)	(0.00204)	(0.00352)	(0.00182)	(0.00405)
District FE	✓	✓	✓	✓	✓	✓	✓	✓
Period FE	✓	✓	✓	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓	✓	✓	✓
Industry shares	✓	✓	✓	✓	✓	✓	✓	✓
Net exports	✓	✓	✓	✓	✓	✓	✓	✓
ICT investment	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1604	1604	1604	1604	1604	1604	1604	1604

Results 1: Long Difference Employment and Wage Effects

Panel A: Employment Changes	(1)	(2)	(3)	(4)	(5)
ΔAI Exposure	0.0104**	**0.0105****			**0.0155*****
	(0.00452)	(0.00452)			(0.00572)
ΔRobot Exposure			0.000929	0.000905	-**0.00351**
			(0.00205)	(0.00204)	(0.00258)
Δ Net exports	No	Yes	No	Yes	Yes
Δ ICT investment	No	Yes	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes
Industry shares	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Observations	401	401	401	401	401

Panel B: Wage Changes	(1)	(2)	(3)	(4)	(5)
ΔAI Exposure	0.000162	0.000175			-**0.000837**
	(0.00169)	(0.00168)			(0.00232)
ΔRobot Exposure			0.000482	0.000471	**0.000709**
			(0.000811)	(0.000806)	(0.00108)
Δ Net exports	No	Yes	No	Yes	Yes
Δ ICT investment	No	Yes	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes
Industry shares	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Observations	401	401	401	401	401

AI Exposure ↑ Employment change ↑ 3%

Robustness Check: Long Difference Employment and Wage Effects excluding German patents

Panel A: Employment Changes	(1)	(2)	(3)	(4)	(5)
ΔAI Exposure	0.0110**	**0.0114****			**0.0155****
	(0.00495)	(0.00493)			(0.00634)
ΔRobot Exposure			0.00120	0.00125	-**0.00272**
			(0.00292)	(0.00202)	(0.00255)
Δ Net exports	No	Yes	No	Yes	Yes
Δ ICT investment	No	Yes	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes
Industry shares	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Observations	401	401	401	401	401

Panel B: Wage Changes	(1)	(2)	(3)	(4)	(5)
ΔAI Exposure	0.00169	0.00176			**0.00192**
	(0.00244)	(0.00239)			(0.00291)
ΔRobot Exposure			0.000364	0.000390	-**0.0001**
			(0.000938)	(0.000920)	(0.00113)
Δ Net exports	No	Yes	No	Yes	Yes
Δ ICT investment	No	Yes	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes
Industry shares	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes
Observations	401	401	401	401	401

Robustness Check: Period Employment and Wage Effects excluding German patents

Panel A: Employment Changes	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.000286		0.00338	-0.0139***		-0.00529
	(0.00175)		(0.00231)	(0.00330)		(0.00382)
ΔRobot Exposure		-0.00135	-0.00229*		-0.00639***	-0.00485***
		(0.000889)	(0.00118)		(0.00147)	(0.00178)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Panel B: Wage Changes	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.00000182		-0.000657	0.000568		0.00444*
	(0.00105)		(0.00128)	(0.00227)		(0.00254)
ΔRobot Exposure		0.000226	0.000410		-0.000875	-0.00217**
		(0.000512)	(0.000633)		(0.000913)	(0.00105)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

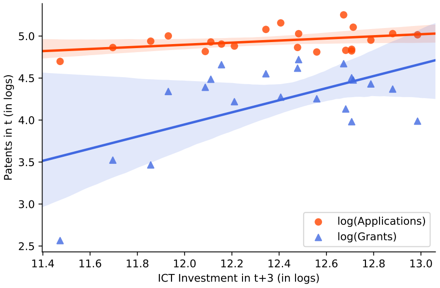
Results 4: Wages Manufacturing vs. Services

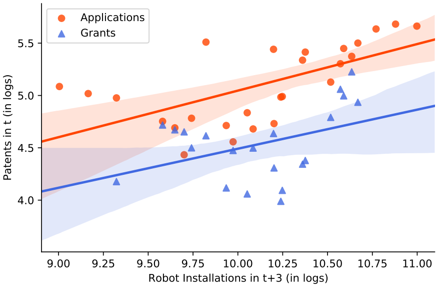
Panel A: Manufacturing Wages						
	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.0000814		-0.000509	-0.00586*		-0.00401
	(0.00141)		(0.00172)	(0.00326)		(0.00422)
ΔRobot Exposure		0.000129	0.000285		-0.00249	-0.00115
		(0.000674)	(0.000839)		(0.000170)	(0.00224)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Panel B: Non-Manufacturing Wages						
	(1)	(2)	(3)	(4)	(5)	(6)
ΔAI Exposure	-0.000926		-0.00268**	-0.00220		-0.00188
	(0.000817)		(0.00105)	(0.00153)		(0.00215)
ΔRobot Exposure		0.000348	0.00118***		-0.000829	-0.000201
		(0.000335)	(0.000436)		(0.000731)	(0.00103)
District FE	No	No	No	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry employment shares	Yes	Yes	Yes	Yes	Yes	Yes
Δ Net exports	Yes	Yes	Yes	Yes	Yes	Yes
Δ ICT investment	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604

Correlations of patents, ICT and IFR

- AI: compare to ICT investment (KLEMS database)
- Robotics: compare to robot installations (IFR database)
- Account for diffusion with 3-year time lag





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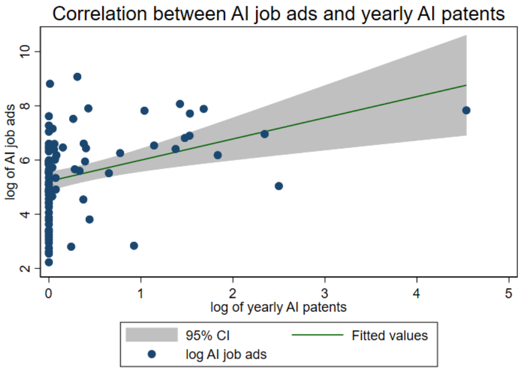
Correlation of AI patents and job vacancies



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