AI and Jobs: Evidence from Online Vacancies

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Question

- Lots of excitement / hype about Artificial Intelligence
- Lots of speculation about how it will transform labor markets, raise productivity, replace workers, destroy humanity in service of making paperclips (Bostrom '14), etc.
- It may be that:
 - there is not as much AI as presumed
 - it is replacing some jobs and transforming labor markets
 - ▶ it is helping create new products, services, occs & industries
 - it is benefiting some organizations without replacing jobs
 - it is too early to tell
- But little evidence so far; we just don't know how Al is being deployed and used in commercial applications
- Limited data on AI adoption or investment

This Paper

- Idea #1: measure AI from its "footprint" in posted jobs
 - Al adoption requires in-house specialists, and these demands can be observed in job postings
- Idea #2: Classify establishments as "AI exposed" if their workers engage in tasks compatible with current capabilities of AI
- Use a comprehensive data set of all online vacancies from BurningGlass Technologies from 2007 to 2018 to study:
 - ▶ whether there has been a major increase in AI activities as proxied by vacancies in AI
 - whether establishments with the greatest AI exposure are in fact adopting AI
 - whether establishments adopting AI have started posting fewer non-AI jobs
 - whether AI-exposed establishments have expanded / contracted or changed their demand for skills

Summary of Results: Rising Adoption of AI Technologies

- Steep recent increase in AI vacancy postings across the economy
- Concentrated in sectors that are "producers and suppliers" of AI (Information Technologies and Business Services—sectors 51 and 54)
- But also significant rise in adoption of AI technologies in other sectors
- Outside of sectors 51 and 54, AI exposed establishments have particularly strong increase in AI vacancies

Summary of Results: Effects on Jobs

- Results are consistent with a **task based view** of AI:
 - 1. Al exposed establishments increase demand for new skills and reduce demand for old skills
 - 2. Al exposed establishments reduce non-Al vacancies, especially after 2014
 - 3. By contrast: no discernible relationship at the occupation + industry level between AI exposure and employment or wages
- **Summary judgment:** Al is replacing humans in a subset of tasks but not yet having detectable aggregate labor market consequences.

Related Literature

- Literature measuring occupations where AI can be used
 - Felten et al. (2018), Brynjolfsson et al. (2018), and Webb (2019)
 - We use these measures to identify opportunities for AI adoption across US establishments and sectors.
- Literature exploring how AI is being deployed by businesses
 - Survey of Al startups by Bessen et al. (2018)
 - We provide evidence that AI is adopted in occs where tasks are compatible with current capabilities of AI
- Literature on effects of AI on specific occupations and sectors
 - Research on financial analysts by Grennan and Michaely (2019)
 - Babina et al. (2020) find that Al-adopting firms grow rapidly
 - We focus on AI suitability rather than observed AI adoption—may explain why we reach different conclusions
- Burgeoning literature using Burning Glass data (Hazell and Taska 2018; Hershbein and Kahn, 2018; Deming and Noray, 'forth QJE; Dillender and Forsythe, 2019; Steffen, 2019; Modestino, Shoag, and Ballance, 2016, 2019)

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Burning Glass Data Measuring AI Suitability in Occupations

Conceptual Framework: What Should We Expect?

Empirical Strategy

Results

Result 1: Al Postings Rise in Establishments with Al-Exposed Occupational MixResult 2: Al Exposure Predicts Demand for New Skills by EstablishmentsResult 3: Al Exposure Predicts Decline Establishments' in Non-Al Vacancy PostingsResult 4: Al Exposure Does Not Predict Aggregate Emp or Wage Changes

- Two main empirical ingredients:
 - 1. Data on vacancy postings, from Burning Glass Technologies (BGT)
 - 2. Classification of occupations according to their 'AI exposure', measured using three indexes

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Burning Glass Data

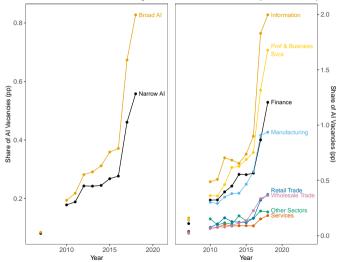
- Burning Glass Technologies: near-universe of online US vacancies
 - Available for years 2007 and 2010-2018
 - Vacancies scraped from 40,000 company websites and online job boards, with de-duplication algorithm
 - Covers 60-80% of all US vacancies, online and offline
 - Detailed information on location, employer, industry, occupation and 'skill' requirements of vacancy
 - Skills, scraped from text, are organized according to several thousand standardized fields
 - Groups of related skills collected together into "skill clusters"

Inferring Adoption of AI from Job Postings

- Narrow AI vacancies: vacancy posting requires one of these skills
 - machine learning, deep learning, neural networks, natural language processing, virtual agents, machine translation and others ...
- Broad AI vacancies: posting associated with skill clusters
 - ▶ natural language processing, data science, artificial intelligence, or machine learning

Al Adoption Rising in the US Economy

Share of AI Vacancies in Burning Glass Share of AI Vacancies by Broad Industry



Narrow AI vacancies up from 0.1% to 0.6%

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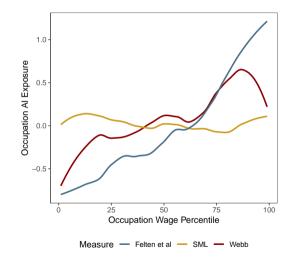
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Occupations with Greatest Potential for Adoption of Al

- Use three occ-level measures—each linked to 6-digit SOC
 - Designed to capture occupations concentrating in tasks that are compatible with the current capabilities of AI
 - 1) Felten, Raj, and Seamans '18:
 - studies tasks where AI has improved in recent years (e.g. image recognition, strategy games, speech recognition)
 - based on AI Progress Measurement project, Electronic Frontier Foundation, starting 2010
 - links tasks to abilities required by detailed occupations in O*NET
 - 2) Webb '19:
 - identifies key capabilities of AI from text in patent data
 - matches capabilities to abilities required by O*NET occupations
 - 3) Brynjolfsson, Mitchell and Rock '19: Suitability for Machine Learning (SML)
 - 21-item rubric of tasks suitable for machine learning/AI
 - Identify AI exposed occupations according to rubric, once again mapped from O*NET data

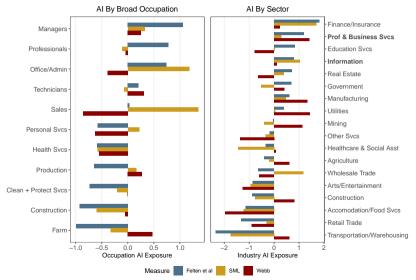
Occupations with Greatest Potential for Adoption of AI



Al exposure by baseline wage in each occupation, standardized

Occupations with Greatest Potential for Adoption of AI

Meaningful Differences Across Measures, Esp. in Managerial, Office/Admin, Sales



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AI and Tasks

- Focus on one key aspect of AI: advancing capacity of AI to perform specific tasks
- How does the ability to perform these tasks with AI affect establishments and workers engaged in those tasks?
- Complementary AI: use of AI will complement workers in the tasks where it is being deployed, raising relative demand for their skills

 (i.e., assessments of radiologist and AI are complementary)
- Replacing AI: use of AI will displace workers from the tasks where it is being deployed, reducing the relative demand for their skills

(i.e., financial analysts out-competed by algorithms)

AI and Tasks

Output of an establishment, y_i, produced by combining services, y_i(x), of a unit measure of tasks x ∈ [0, 1]:

$$\ln y_i = \int_0^1 \alpha_i(x) \ln y_i(x) dx, \text{ where } \int_0^1 \alpha_i(x) dx = 1$$
 (1)

- $\alpha_i(x)$: intensity of task x in establishment's *i* production
- Tasks produced by human labor, $\ell(x)$, or by AI algorithms, a(x):

$$y_i(x) = \left[\left(\gamma_\ell(x) \ell_i(x) \right)^{\frac{\sigma-1}{\sigma}} + \left(\gamma_a(x) a_i(x) \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$
(2)

• Think of AI as increases in $\gamma_a(x)$ in certain tasks, which will benefit establishments engaged intensively in these tasks

 Complementary view assumes that σ < 1, so that algorithms and labor are complements in producing y(x)

▶ Let workers in occupation o specialize on tasks in $\mathcal{T}_o \subset [0,1]$

- Following an improvement in $\gamma_a(x)$ for tasks in \mathcal{T}_o :
 - 1. complementary AI will increase the share of employment in AI-exposed occupations
 - 2. establishments engaged in these tasks will adopt more AI and increase their employment

Replacing AI

Substitution view

- ▶ Take $\sigma = \infty$, so that tasks are performed by labor or algorithms
- ▶ Displacement effects: consider improvements in $\gamma_a(x)$ for tasks in $\mathcal{T}_o \subset [0, 1]$
- This process has the following implications:
 - 1. replacing AI will reduce the share of employment in AI-exposed occupations
 - 2. establishments engaged in these tasks will adopt more AI with ambiguous effects on their employment

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Exposure to Opportunities for AI Adoption

the

• Al exposure measure at the establishment level, e:

AI exposure_{$$et_0$$} = \sum_{o} Share postings _{eot_0} × Occupation AI Score_o

- Share postings_{eot0} in 2010
- Occupation AI Score, from Felten et al, Webb, or SML
- Summation runs over 815 detailed occupations, o
- Establishments with a higher AI exposure_{st0} have greater opportunities to adopt AI as algorithms improve
- We standardize exposure measure across establishments to facilitate interpretation

Empirical Strategy

• Empirical models at the establishment level:

 $\Delta Y_{s} = \beta \cdot \text{AI exposure}_{st_{0}} + \theta X_{s} + \alpha_{f(s)} + \delta_{i(s)} + \eta_{z(s)} + \varepsilon_{s}$

- ΔY_s : change in outcome between 2010-2012 and 2016-2018
- X_s : parent firm size deciles
- $\alpha_{f(s)}$: firm fixed effects in some specifications
- $\delta_{i(s)}$: industry fixed effects (at 3-digit for 85% of sample)
- $\eta_{z(s)}$: commuting-zone fixed effects
- Exclude sectors 51 and 54—producers and suppliers of AI
- β : is the differential effect of AI on establishments concentrated in AI suitable tasks

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Establishment Share of AI Vacancies by Quartile of AI Exposure

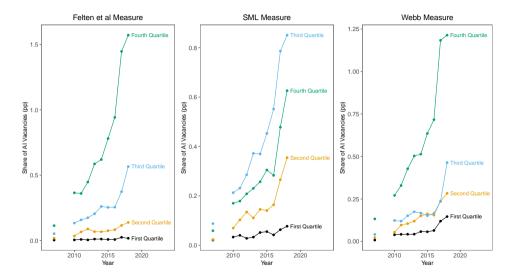
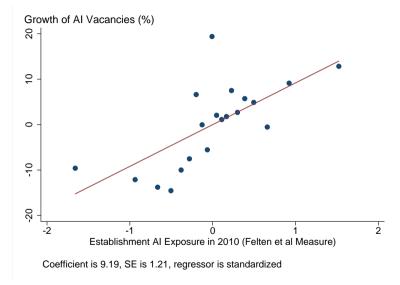


Table 1: Opportunities for Adoption and AI Postings

	Growth of Establishment Al Vacancies, 2010-2018						
	(1)	(2)	(3)	(4)	(5)	(6)	
	Panel A: Felten et al. Measure of AI Exposure						
Establishment Al	15.96***	13.82***	9.19***	16.53***	9.75***	16.87***	
Exposure, 2010	(1.73)	(1.43)	(1.21)	(1.89)	(1.20)	(1.86)	
Observations	1,075,474	1,075,474	954,519	770,461	954,518	762,672	
Firm Size Decile		\checkmark	\checkmark		\checkmark		
Commuting Zone		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
3 digit Industry			\checkmark		\checkmark		
Firm				\checkmark		\checkmark	
Sales + Admin Share					\checkmark	\checkmark	

- One standard deviation in AI exposure ightarrow 16% increase in 2010-2018 AI postings

2010-2018 Growth of AI and 2010 Establishment Felten et al Score



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Measuring Effects of AI Exposure on Demand for Skills

- Does AI exposure reduce demand for old skills? Or increase demand for new skills?
 - Build on approach from Deming & Noray (QJE forth.)

Measuring Effects of AI Exposure on Demand for Skills

- Does AI exposure reduce demand for old skills? Or increase demand for new skills?
 - Build on approach from Deming & Noray (QJE forth.)
- We measure changing skill demand within non-AI jobs at establishment level:

measures decline in frequency of certain previously posted skills

$$\text{positive skill change}_{e,t_2,t_1} = \max\left\{\sum_{s=1}^{S} \left[\left(\frac{\text{skill}_{e,t_2}^s}{\text{vacancies}_{e,t_2}} \right) - \left(\frac{\text{skill}_{e,t_1}^s}{\text{vacancies}_{e,t_1}} \right) \right], 0 \right\}$$

measures increase in frequency of other previously posted skills (including new skills)

Table 2a: AI Exposure Predicts Lower Demand for Certain Skills

	Establishment Negative Skill Change, 2010-2018			
	(1)	(2)	(3)	(4)
	Pane	<i>A:</i> Felten et al. N	Measure of AI Exp	osure
Establishment Al	0.83***	0.83***	0.97***	0.50***
Exposure, 2010	(0.09)	(0.09)	(0.07)	(0.05)
Observations	339,282	339,282	322,901	339,282
	P	anel B: Webb Mea	sure of AI Exposu	re
Establishment Al	0.62***	0.60***	0.45***	0.20***
Exposure, 2010	(0.11)	(0.11)	(0.06)	(0.04)
Observations	353,107	353,107	335,589	353,107
	F	Panel C: SML Mea	sure of AI Exposur	e
Establishment Al	0.53***	0.52***	0.32***	0.26***
Exposure, 2010	(0.08)	(0.07)	(0.07)	(0.04)
Observations	353,107	353,107	335,589	353,107
Firm Size Decile		\checkmark	\checkmark	
Commuting Zone		\checkmark	\checkmark	\checkmark
3 digit Industry			\checkmark	
Firm				\checkmark

Mean Establishment Negative Skill Change is 4.70

Table 2b: AI Exposure Predicts Higher Demand for Certain Skills

	Establishment Positive Skill Change, 2010-2018				
	(1)	(2)	(3)	(4)	
	Panel A: Felten et al. Measure of AI Exposure				
Establishment Al	0.95***	0.94***	0.58***	0.02	
Exposure, 2010	(0.08)	(0.09)	(0.09)	(0.04)	
Observations	339,282	339,282	322,901	339,282	
	P	anel B: Webb Mea	asure of AI Exposu	re	
Establishment Al	0.69***	0.66***	0.26***	-0.01	
Exposure, 2010	(0.09)	(0.09)	(0.08)	(0.03)	
Observations	353,107	353,107	335,589	353,107	
	Panel C: SML Measure of AI Exposure				
Establishment Al	0.62***	0.59***	0.19**	0.10**	
Exposure, 2010	(0.09)	(0.09)	(0.09)	(0.04)	
Observations	353,107	353,107	335,589	353,107	
Firm Size Decile		\checkmark	\checkmark		
Commuting Zone		\checkmark	\checkmark	\checkmark	
3 digit Industry			\checkmark		
Firm				\checkmark	

Mean Establishment Positive Skill Change is 6.30

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Table 3: AI Exposure Predicts Decline in Non-AI Vacancy Postings

Effects of AI Exposure on Establishment Non-AI Vacancy Growth

	2010-2014 Growth			2014-2018 Growth				
	(1)	(2)	(3)	(4)	(5)	(6)		
	Panel A: Felten et al. Measure of AI Exposure							
Establishment Al	-1.86	-1.82	0.39	-11.94***	-10.60***	-5.21***		
Exposure, 2010	(4.77)	(3.46)	(1.11)	(3.80)	(2.82)	(1.02)		
Observations	1,075,474	954,519	1,075,474	1,075,474	954,519	1,075,474		
Firm Size Decile		\checkmark			\checkmark			
Commuting Zone		\checkmark	\checkmark		\checkmark	\checkmark		
3 digit Industry		\checkmark			\checkmark			
Firm			\checkmark			\checkmark		
Sales + Admin Share		\checkmark			\checkmark			

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Table 4: AI Exposure and Occupational Employment and Wage Growth

Effects of AI Exposure on Occupation-Level Outcomes

	2010-2018 Occupation Employment Growth	2010-2018 Occupation Wage Growth		
	(1)	(2)		
	Panel A: Felten et a	I. AI Exposure		
Occurrentian AL European 2010	0.51	-0.17***		
Occupation AI Exposure, 2010	(0.35)	(0.06)		
Observations	680	629		
	Panel B: Webb AI Exposure			
Occurrentian AL England 2010	-0.17	-0.02		
Occupation AI Exposure, 2010	(0.29)	(0.04)		
Observations	717	663		
	Panel C: SML A	Exposure		
Operation AL England 2010	-0.37	0.04		
Occupation AI Exposure, 2010	(0.25)	(0.05)		
Observations	717	663		
3 Digit Occupation	\checkmark	\checkmark		

Employment and Wage Growth from Occupational Employment Statistics (Industry Results)

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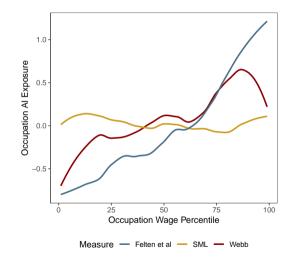
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Conclusion

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- Much excitement and apprehension about AI and its labor market effects
 - We document a recent surge in AI activity
- Results are consistent with a **task based** view of AI:
 - 1. Al adoption driven by "Al exposed" establishments
 - 2. Al exposed establishments increase demand for new skills
 - 3. Al exposed establishments reduce non-Al vacancies, especially after 2014
 - 4. By contrast: no discernible effect of AI exposure at occupation + industry level
- **Summary judgment:** Al is replacing humans in a subset of tasks but not yet having detectable aggregate labor market consequences.

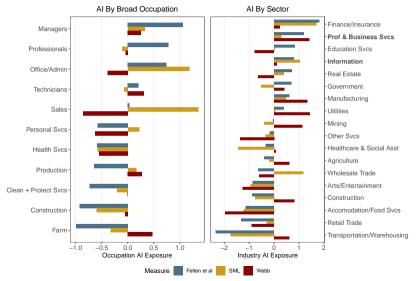
Occupations with Greatest Potential for Adoption of AI Return



Al exposure by baseline wage in each occupation, standardized

Occupations with Greatest Potential for Adoption of AI

Meaningful Differences Across Measures, Esp. in Managerial, Office/Admin, Sales



Robustness: Webb and SML Scores Predicts AI

Relationship Between AI Exposure and Establishment AI Vacancy Growth

	Growth of Establishment AI Vacancies, 2010-2018						
	(1)	(2)	(3)	(4)	(5)	(6)	
	Panel B: Webb Measure of AI Exposure						
Establishment Al	6.59***	5.08***	3.21***	5.91***	0.42	1.14	
Exposure, 2010	(1.13)	(0.96)	(0.81)	(1.27)	(0.82)	(1.08)	
Observations	1,159,789	1,159,789	1,021,673	827,340	1,021,673	824,803	
		Pan	el C: SML Meas	sure of AI Exp	osure		
Establishment Al	3.76***	2.30**	-2.21**	-3.04**	1.95**	4.47***	
Exposure, 2010	(1.19)	(1.04)	(0.96)	(1.38)	(0.89)	(1.34)	
Observations	1,159,789	1,159,789	1,021,673	827,340	1,021,673	824,803	
Firm Size Decile		\checkmark	\checkmark		\checkmark		
Commuting Zone		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
3 digit Industry			\checkmark		\checkmark		
Firm				\checkmark		\checkmark	
Sales + Admin Share					\checkmark	\checkmark	

Robustness: Al Share Change as Outcome

Relationship Between AI Exposure on Establishment AI Share Change

		Change in Sha	re of Establishr	ment Al Vacano	ies, 2010-2018		
	(1)	(2)	(3)	(4)	(5)	(6)	
	Panel A: Felten et al Measure of Al Exposure						
Establishment Al	0.29***	0.26***	0.20***	0.18***	0.22***	0.18***	
Exposure, 2010	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Observations	341,525	341,525	324,901	299,602	324,901	299,602	
		Pane	el B: Webb Mea	asure of AI Exp	osure		
Establishment Al	0.25***	0.22***	0.14***	0.11***	0.12***	0.05**	
Exposure, 2010	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	
Observations	355,529	355,529	337,758	311,012	337,758	311,012	
		Pan	el C: SML Mea	sure of AI Expo	osure		
Establishment Al	0.05***	0.03**	-0.06***	-0.08***	0.04**	0.05***	
Exposure, 2010	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	
Observations	355,529	355,529	337,758	311,012	337,758	311,012	
Firm Size Decile		\checkmark	\checkmark		\checkmark		
Commuting Zone		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
3 digit Industry			\checkmark		\checkmark		
Firm				\checkmark		\checkmark	
Sales + Admin Share					\checkmark	\checkmark	

Robustness: Establishment AI Exposure in 2007

Relationship Between AI Exposure in 2007 and Establishment AI Growth

	Gr	Growth of Establishment AI Vacancies, 2010-2018					
	(1)	(2)	(3)	(4)	(5)	(6)	
		Panel A: Fe	lten et al N	Aeasure of	AI Exposur	e	
Establishment Al	23.32***	20.43***	12.20***	15.24***	12.07***	13.68***	
Exposure, 2007	(2.33)	(1.98)	(1.78)	(2.04)	(1.74)	(1.88)	
Observations	102,783	102,783	101,553	99,078	101,524	94,866	
		Panel B:	Webb Mea	asure of AI	Exposure		
Establishment Al	8.87***	6.97***	4.49***	5.04***	1.92	2.48**	
Exposure, 2007	(1.71)	(1.54)	(1.33)	(1.39)	(1.30)	(1.20)	
Observations	106,022	106,022	104,719	102,158	104,688	97,919	
		Panel C.	SML Mea	sure of AI I	Exposure		
Establishment Al	7.46***	5.44***	-1.66	-3.39*	1.78	-0.68	
Exposure, 2007	(1.99)	(1.78)	(1.57)	(1.82)	(1.44)	(1.64)	
Observations	106,022	106,022	104,719	102,158	104,688	97,919	
Firm Size Decile		\checkmark	\checkmark		\checkmark		
Commuting Zone		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
3 digit Industry			\checkmark		\checkmark		
Firm				\checkmark		\checkmark	
Sales + Admin Share					\checkmark	\checkmark	

Robustness: Effect of of Webb and SML AI Exposure on Non-AI Vacancies

Effects of AI Exposure on Establishment Non-AI Vacancy Growth, 2010-2018

	Growth of Non-AI Establishment Vacancies, 2010-2018							
	(1)	(2)	(3)	(4)	(5)	(6)		
	Panel B: Webb Measure of AI Exposure							
Establishment Al	-17.24***	-18.21***	-6.73**	-2.22**	-8.30**	1.51		
Exposure, 2010	(3.72)	(3.63)	(3.01)	(0.93)	(3.70)	(0.98)		
Observations	1,159,789	1,159,789	1,021,673	827,340	1,021,673	827,340		
		1	Panel C: SML Meas	sure of AI Exposu	re			
Establishment Al	7.02**	5.74*	2.05	0.95	2.21	-3.01**		
Exposure, 2010	(3.13)	(3.01)	(2.92)	(1.16)	(3.61)	(1.22)		
Observations	1,159,789	1,159,789	1,021,673	827,340	1,021,673	827,340		
Covariates:								
Share of Vacancies in					\checkmark	\checkmark		
Sales, Admin. in 2010								
Fixed Effects:								
Firm Size Decile		\checkmark	\checkmark		\checkmark			
Commuting Zone		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark		
3 digit Industry			\checkmark		\checkmark			
Firm				\checkmark		\checkmark		

Non-AI Vacancy Growth over 2010-2018

Effects of AI Exposure on Establishment Non-AI Vacancy Growth, 2010-2018

	Growth of Establishment Non-Al Vacancies, 2010-2018						
	(1)	(2)	(3)	(4)	(5)	(6)	
		Pane	I A: Felten et al.	Measure of AI Exp	osure		
Establishment Al	-13.80***	-16.36***	-11.90***	-4.81***	-12.42***	-4.04***	
Exposure, 2010	(4.22)	(4.11)	(4.08)	(1.44)	(4.01)	(1.47)	
Observations	1,075,474	1,075,474	954,519	1,075,474	954,519	1,075,474	
Covariates:							
Share of Vacancies in					\checkmark	\checkmark	
Sales, Admin. in 2010							
Fixed Effects:							
Firm Size Decile		\checkmark	\checkmark		\checkmark		
Commuting Zone		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
3 digit Industry			\checkmark		\checkmark		
Firm				\checkmark		\checkmark	

Robustness: AI Exposure Predicts Lower Demand for Certain Skills

	Establishment Negative Skill Change, 2010-2018								
	(1)	(2)	(3)	(4)	(5)	(6)			
	Panel B: Webb Measure of AI Exposure								
Establishment Al	0.62***	0.60***	0.45***	0.20***	0.68***	0.34***			
Exposure, 2010	(0.11)	(0.11)	(0.06)	(0.04)	(0.11)	(0.04)			
Observations	353,107	353,107	335,589	353,107	335,589	353,107			
	Panel C: SML Measure of AI Exposure								
Establishment Al	0.53***	0.52***	0.32***	0.26***	0.46***	0.36***			
Exposure, 2010	(0.08)	(0.07)	(0.07)	(0.04)	(0.09)	(0.04)			
Observations	353,107	353,107	335,589	353,107	335,589	353,107			
Firm Size Decile		\checkmark	\checkmark		\checkmark				
Commuting Zone		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark			
3 digit Industry			\checkmark		\checkmark				
Firm				\checkmark		\checkmark			
Sales + Admin Share					\checkmark	\checkmark			

Effects of AI Exposure on Establishment Negative Skill Change, 2010-2018

Return

Robustness: AI Exposure Predicts Higher Demand for Certain Skills

	Establishment Positive Skill Change, 2010-2018						
	(1)	(2)	(3)	(4)	(5)	(6)	
		F	anel B: Webb Mea	asure of AI Exposu	re		
Establishment Al	0.69***	0.66***	0.26***	-0.01	0.43***	0.13***	
Exposure, 2010	(0.09)	(0.09)	(0.08)	(0.03)	(0.08)	(0.04)	
Observations	353,107	353,107	335,589	353,107	335,589	353,107	
	Panel C: SML Measure of AI Exposure						
Establishment Al	0.62***	0.59***	0.19**	0.10**	0.26***	0.03	
Exposure, 2010	(0.09)	(0.09)	(0.09)	(0.04)	(0.09)	(0.04)	
Observations	353,107	353,107	335,589	353,107	335,589	353,107	
Firm Size Decile		\checkmark	\checkmark		\checkmark		
Commuting Zone		\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
3 digit Industry			\checkmark		\checkmark		
Firm				\checkmark		\checkmark	
Sales + Admin Share					\checkmark	\checkmark	

Effects of AI Exposure on Establishment Positive Skill Change, 2010-2018

Return

Table 4b: AI Exposure and Industry-by-CZ Employment Growth Reum

	Industry by	CZ Employm	ent Growth
	2003-2007	2007-2010	2010-2016
	(1)	(2)	(3)
	Panel A: F	elten et al. A	I Exposure
Market AI Exposure,	0.03	0.10	-0.05
2010	(0.17)	(0.20)	(0.08)
Observations	10,937	10,926	10,929
	Panel E	3: Webb AI E	xposure
Market AI Exposure,	0.10	0.18	0.11
2010	(0.15)	(0.17)	(0.09)
Observations	10,981	10,968	10,968
	Panel	C: SML AI E>	posure
Market AI Exposure,	-0.14	0.37**	-0.01
2010	(0.17)	(0.18)	(0.08)
Observations	10,981	10,968	10,968
Commuting Zone	\checkmark	\checkmark	\checkmark
Sector	\checkmark	\checkmark	\checkmark

Employment Growth is from County Business Patterns