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DO ROBOTS INCREASE WAGES?

A topic modeling approach at individual and metropolitan levels

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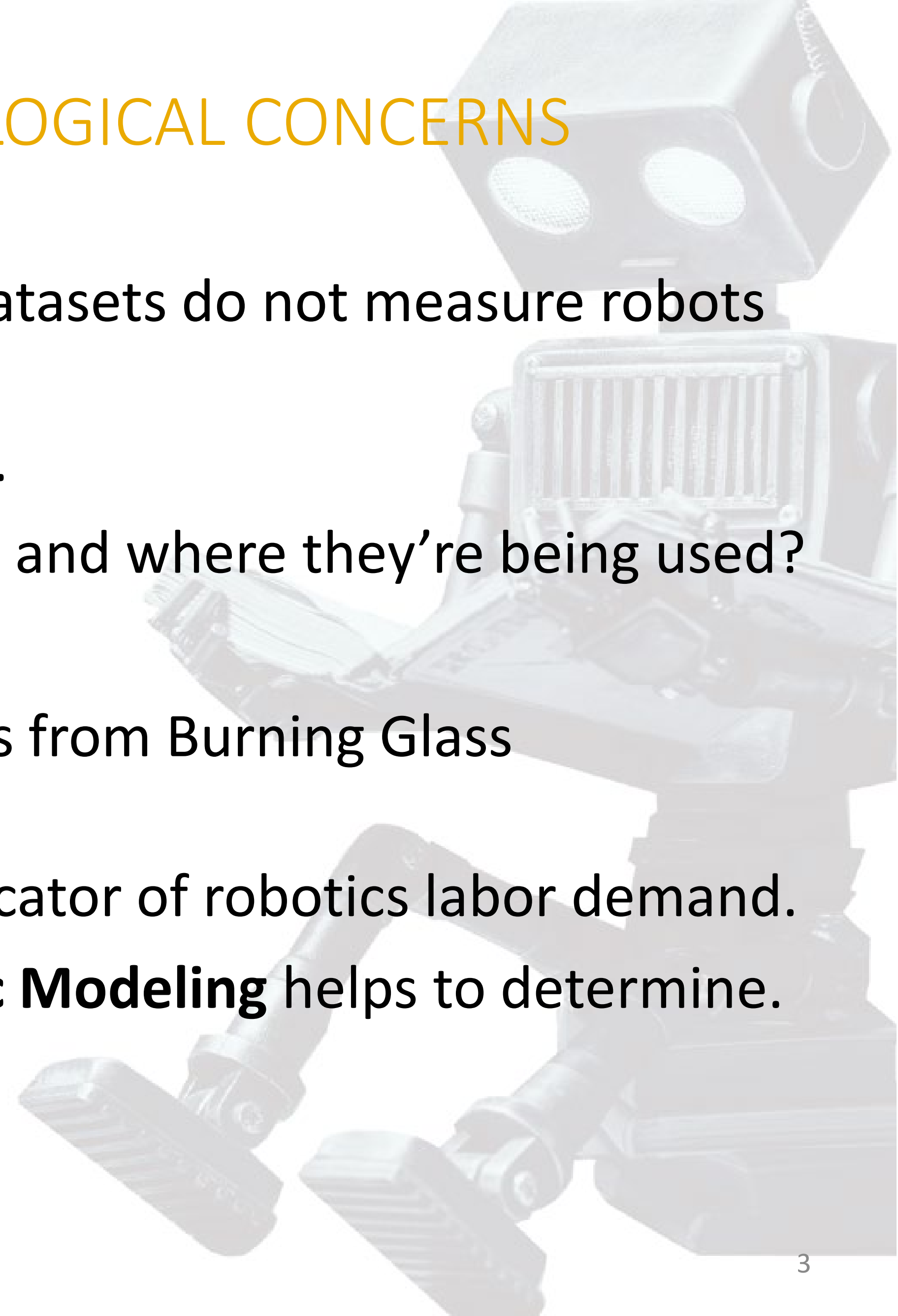
INTRODUCTION*

- Part of project trying to “dig deeper” into robot use and economic impacts.
- Introduce a new methodology called topic modeling, applied to text of job ads
- Test to determine robotics labor demand effects on wages
- Results:
    - Determine three distinct categories of robotics jobs in US manufacturing.
    - Two “higher skill” categories raise wages individually and regionally; “lower skill” category has no effect on wages.
    - Effects are similar at both individual and metropolitan levels.

    - *Research supported by National Science Foundation Award #1637737
    - NRI: Workers, Firms and Industries in Robotic Regions

ROBOTS AND JOBS: EPISTEMOLOGICAL CONCERNS



- Standard public socio-economic datasets do not measure robots or robot use.
- Robotics data is highly aggregated.
- How do we know who uses robots and where they're being used?

- We use Online Job Advertisements from Burning Glass Technologies (BGT)
- Use text of advertisements as indicator of robotics labor demand.
- But how do we use the text? **Topic Modeling** helps to determine.

ECONOMIC IMPACTS OF ROBOTICS RESEARCH

- Research is limited and there is no consensus; falls into two categories:

The "Robocalypse"

- Frey & Osborne, 2013
- Acemoglu & Restrepo, 2017

The Status Quo

- Jäger et al, 2015
- Graetz & Michaels, 2015

“ROBOCALYPSE” RESEARCH

Authors	Year	Title	Major Findings
Frey & Osborne	2013	The Future of Employment: How Susceptible are Jobs to Computerization	47% of current occupations are at high risk of automation
Acemoglu & Restrepo	2017	Robots and Jobs: Evidence from U.S. Labor Markets	One robot/thousand workers decreases employment by 3 to 6 workers and aggregate wages by .25 to .75%.

STATUS QUO RESEARCH

Authors	Year	Title	Major Findings
Graetz & Michaels	2015	Robots at Work	Robots increase labor productivity and value added. No effect on overall number of production hours worked; slight reduction in lower-skill hours.
Jäger et al.	2015	Analysis of the Impact of Robotic Systems on Employment in the EU	Robots increase labor productivity but have no effect on employment. Robot use is associated with decreased likelihood to offshore production.

APPROACHES TO MEASURING ROBOT USE

Author	Name of Measure	Operationalization	Data Source
Jäger et al.	Intensity of Robot Use	Qualitative scale: High, Medium, or Low	European Manufacturing Survey 2009
Graetz & Michaels	Robot Density	# of Robots/Thousand Workers (by Country)	International Federation of Robotics' Robot Stocks Data
Acemoglu & Restrepo	Robot Exposure	# of Robots/Thousands of Workers (by Commuting Zone)*	International Federation of Robotics' Robot Stocks Data

*Robot exposure in commuting zones is an inferred statistic, derived by summing, over industries, the local fraction of the workforce in each industry times the national penetration of robots into that industry.

LIMITATIONS OF CURRENT RESEARCH

- Data problems
  - No direct quantitative measure of robot use exists (IFR robot stocks are inferred from sales).
  - Existing IFR data is coarse-grained, aggregated by country and industry.
  - US studies' data panels end at 2007 (prior to Great Recession).
- Conceptual problems
  - Simple models with substantial assumptions.
  - Ignores robotics integration.
  - Ignores subnational variations in robotics diffusion, knowledge, and potential effects (Leigh & Kraft [2017] show that it is substantial in U.S.).
- Geography is important!

DATA

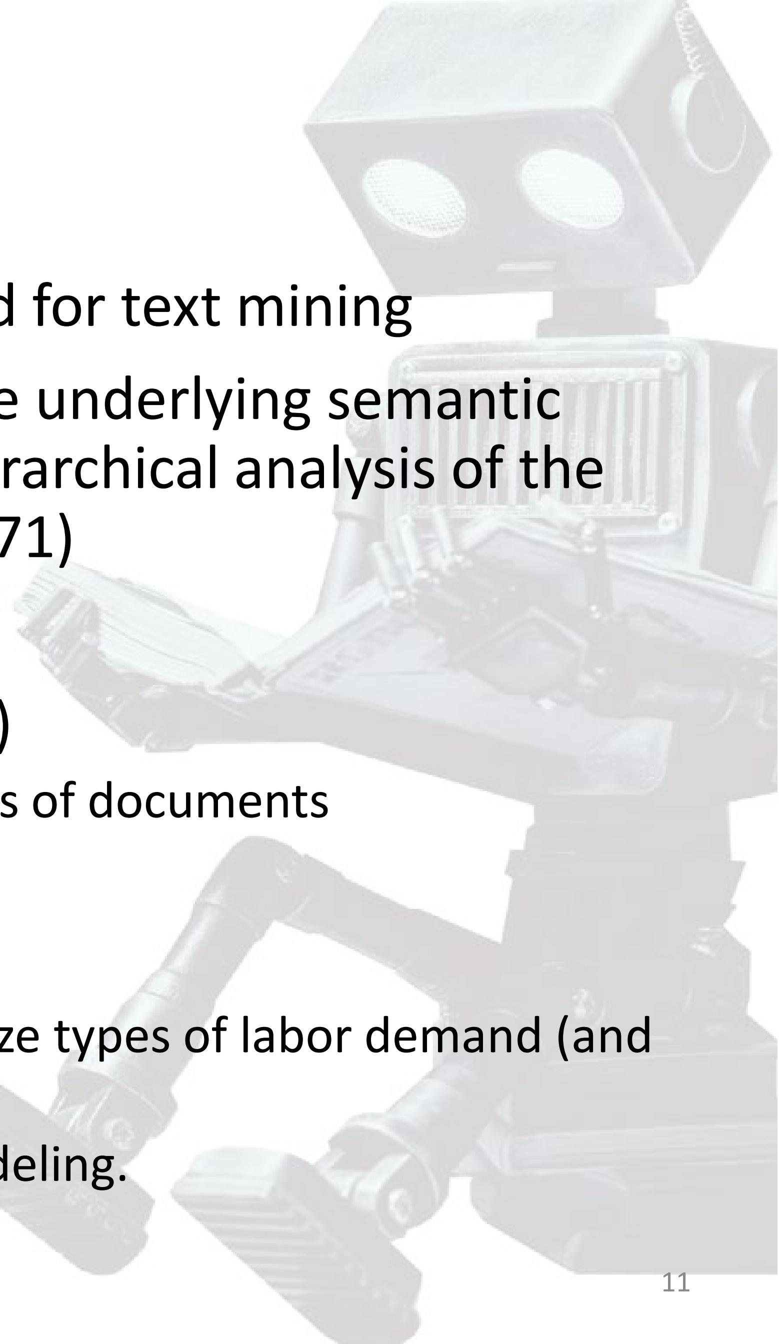
- Real Time Labor Market Information (RTLMI)
  - “Spiders” web for job listings
  - Searchable by skills (i.e. Robotics)
  - We use Burning Glass Technologies
  - Years available: 2007, 2010-2016
  - Not ideal for comparison over time, but best data of its type available
  - We extracted 9,856,829 mfg observations.

TOPIC MODELING

- Unsupervised machine learning method for text mining
- “probabilistic models for uncovering the underlying semantic structure of a document based on a hierarchical analysis of the original texts” (Blei & Lafferty, 2009, p. 71)

- We use Latent Dirichlet Allocation (LDA)
    - Assumes hidden or “latent” topics in corpus of documents
    - Useful for emergent phenomena
- Output is “topics”
    - Topics are useful by themselves to categorize types of labor demand (and should be verified qualitatively).
    - Can also become indicators for further modeling.

TOPIC MODELING



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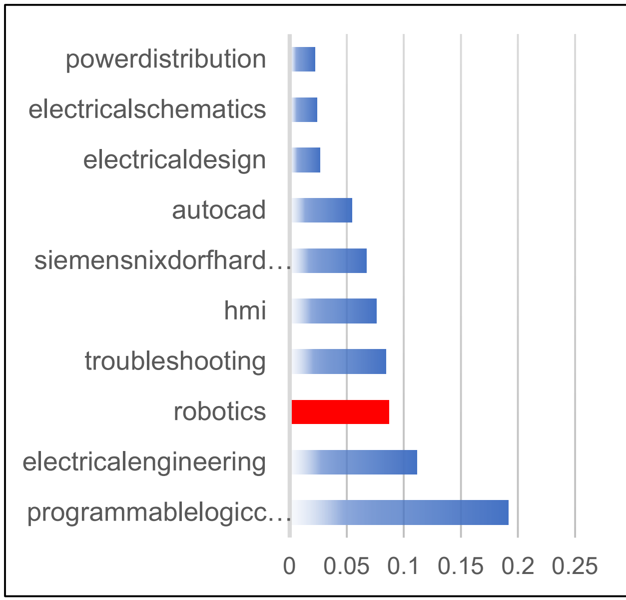
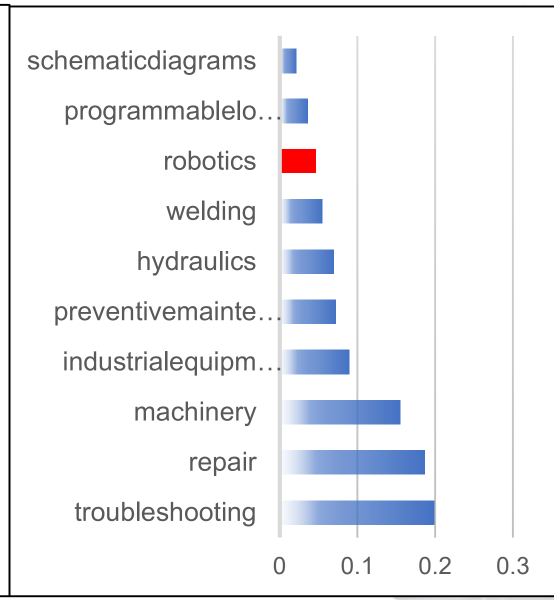
TOPIC MODELING

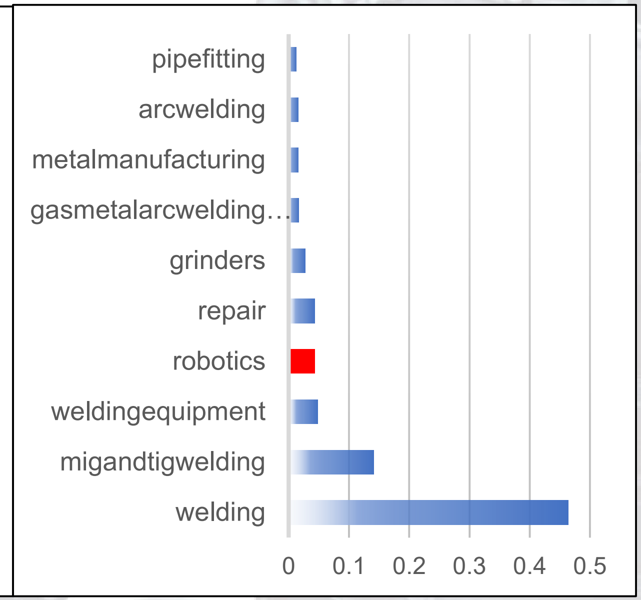
- *K* = number of topics
- Tested *k* = 50 through *k* = 300; used *k* = 100
- High Robotics “Betas” indicate robotics-associated topic
  - Beta is the per-topic-per-word probability



beta * 100 = 8.70%



beta * 100 = 4.35%

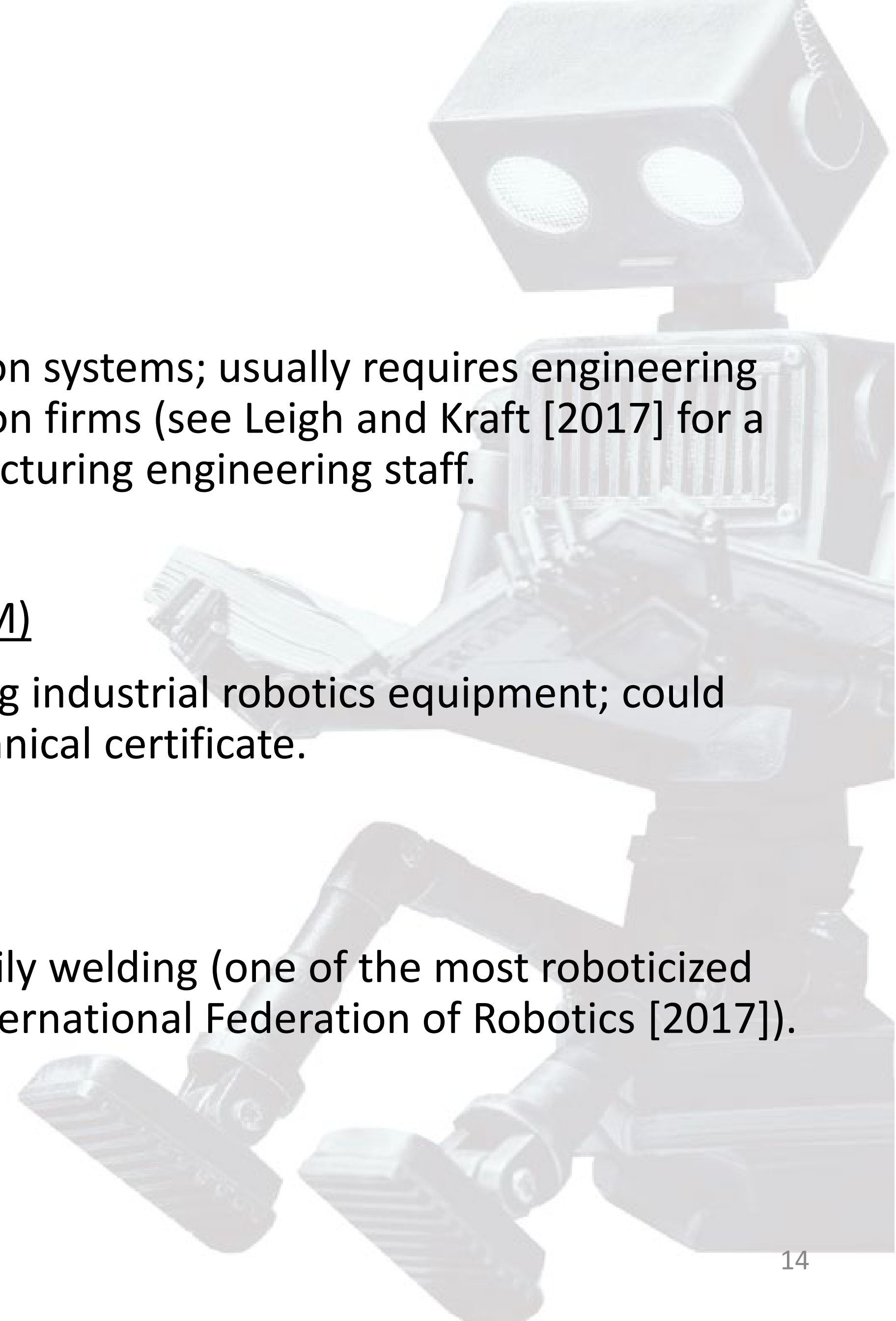


beta * 100 = 4.70%

TOPIC MODELING

Title	System Design & Engineering (SDE)		Machinery Repair & Maintenance (MRM)		Welding & Metal Processing (WMP)	
Top Skills	BGT Skill	Beta	BGT Skill	Beta	BGT Skill	Beta
	Programmable logic controller programming	0.192	Troubleshooting	0.199	Welding	0.464
	Electrical engineering	0.112	Repair	0.187	Tig and mig welding	0.141
	Robotics	**0.087**	Machinery	0.155	Welding equipment	0.049
	Troubleshooting	0.084	Industrial equipment / industry background	0.090	**Robotics**	**0.043**
	Human machine interface	0.076	Preventive maintenance	0.072	Repair	0.043
	Siemens Nixdorf hardware	0.067	Hydraulics	0.070	Grinders	0.027
	AutoCAD	0.054	Welding	0.055	Gas metal arc welding	0.017
	Electrical design	0.027	**Robotics**	**0.047**	Metal manufacturing	0.016
	Electrical schematics	0.024	Programmable logic controller programming	0.036	Arc welding	0.015
	Power distribution	0.022	Schematic diagrams	0.021	Pipe fitting	0.013

ROBOTICS SKILLS TOPICS



Topic 1: System Design & Engineering (SDE)

Designing and implementing robotics automation systems; usually requires engineering degree; performed by robotics system integration firms (see Leigh and Kraft [2017] for a description of integrators) and in-house manufacturing engineering staff.

Topic 2: Machinery Repair & Maintenance (MRM)

Maintaining, repairing, and sometimes operating industrial robotics equipment; could have four-year degree, two-year degree, or technical certificate.

Topic 3: Welding & Metal Processing (WMP)

Operating robotics for metal fabrication, primarily welding (one of the most roboticized industrial functions to date, according to the International Federation of Robotics [2017]).

TOP 5 OCCUPATION GROUPS SORTED BY % OF JOB ADS ALIGNED WITH ROBOTIC-RELATED SKILL TOPICS

Occupation Titles	Avg. Edu. Requirement (BGT years of schooling)	Avg. Exp. Requirement (BGT years of work)	Avg. Min. hourly salary	% of Ads aligned with SDE	% of Ads aligned with MRM	% of Ads aligned with WMP
Sorted by % of Ads aligned with SDE						
Robotics Engineers	15.4	3.8	35.8	**82.9**	30.5	22.9
Mechatronics Engineers	15.8	5.2	37.2	**79.5**	16.7	6.7
Robotics Technicians	13.4	3.9	26.7	69.6	43.5	30.4
Electrical Engineers	16.0	4.7	38.2	68.4	13.7	3.0
Control and Valve Installers and Repairers, Except Mechanical Door	12.9	3.8	27.6	66.8	27.0	14.5
Sorted by % of Ads aligned with MRM						
Robotics Technicians	13.4	3.9	26.7	69.6	**43.5**	30.4
Maintenance Workers, Machinery	12.6	4.6	23.3	15.3	**37.4**	23.7
Installation, Maintenance, and Repair Workers, All Other	12.4	3.5	20.8	18.9	34.7	15.4
Millwrights	12.1	3.8	23.4	5.3	34.6	43.8
Industrial Machinery Mechanics	12.1	2.8	24.5	12.0	34.5	27.4
Sorted by % of Ads aligned with WMP						
Welders, Cutters, and Welder Fitters	12.2	2.5	18.2	1.6	9.6	**95.2**
Pipe Fitters and Steamfitters	12.0	4.1	23.9	2.5	15.5	**90.0**
Layout Workers, Metal and Plastic	12.9	4.0	23.0	0.0	7.1	54.1
Structural Metal Fabricators and Fitters	12.3	2.5	16.7	1.1	8.2	54.0
Millwrights	12.1	3.8	23.4	5.3	34.6	43.8

*O*NET Eight Digit Occupation Titles*

ROBOTICS SKILLS AND WAGES FOR INDIVIDUALS

To determine extent robotics skill demand influences minimum offered hourly wage, used "Mincerian" wage model

$$\ln(minimum\ hourly\ wage_{ij}) = \beta_{0j} + \beta_{1j}EDU_{ij} + \beta_{2j}EXP_{ij} + \beta_{3j}EXP_{ij}^{2} + \sum\beta_{kj}\chi_{kij} + e_i$$

Where
i = individual
j = occupation
k = additional control variable
EDU = education
EXP = experience

Experience is modeled with an exponential term to reflect increasing returns as it is accumulated.
Predicts minimum hourly wage advertised based on ad's alignment with either (or all) of the three skill topics.
Multi-level model accounts for different base wages for different occupations.

Sample: N = 833,792; narrowed from over 10 million based on

- In manufacturing sector
- Has both wage and education information
- Between 2013 and 2017

ROBOTICS SKILLS AND WAGES FOR INDIVIDUALS

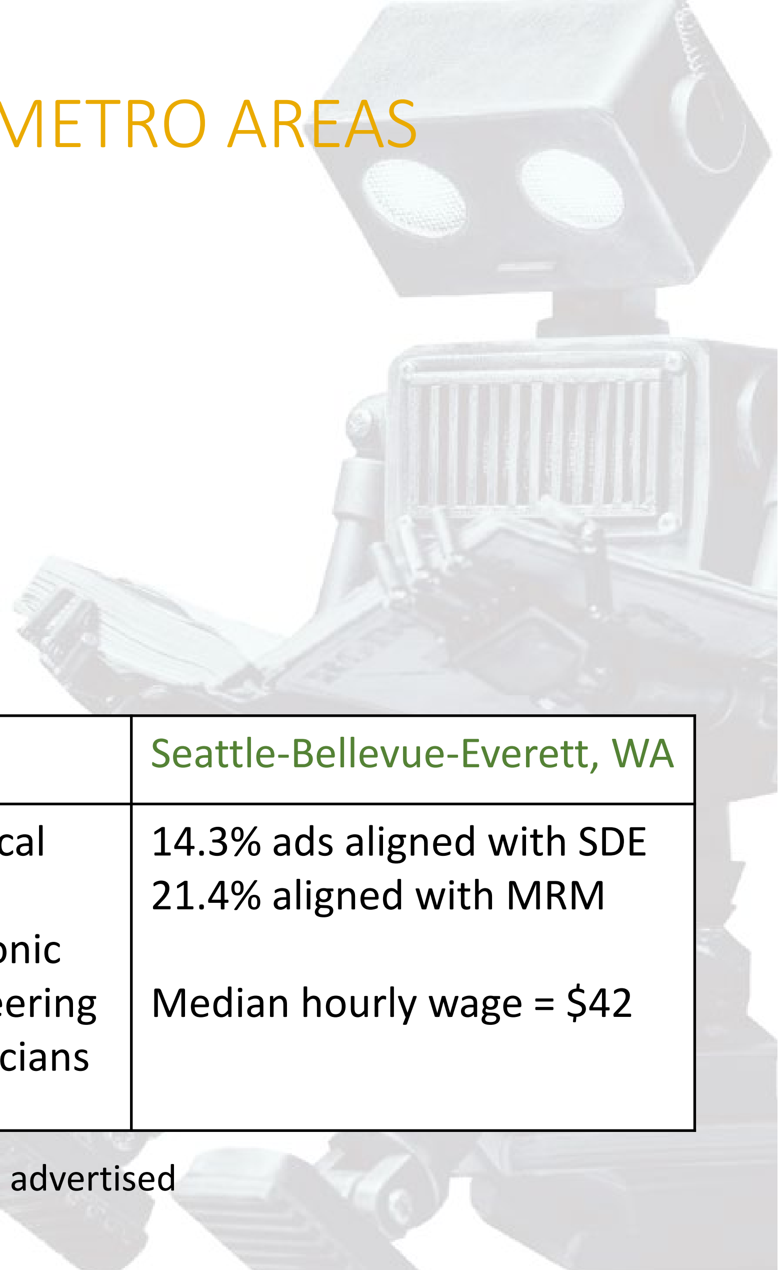
Variables	Base model		Sparse Robot Skill model		Full model	
	Coefficient	Std. Err	Coefficient	Std. Err	Coefficient	Std. Err
Fixed Effects						
Degree requirement						
N/A	0.040***	0.001	0.041***	0.001	0.016***	0.001
Associate's	0.044***	0.003	0.043***	0.003	0.025***	0.003
Bachelor's	0.178***	0.002	0.177***	0.002	0.120***	0.002
Master's	0.251***	0.006	0.251***	0.006	0.173***	0.006
Ph.D.	0.384***	0.013	0.384***	0.013	0.309***	0.013
Experience	0.052***	0.000	0.052***	0.000	0.046***	0.000
Experience squared	-0.002***	0.000	-0.002***	0.000	-0.002***	0.000
Part-time dummy	-0.124***	0.003	-0.123***	0.003	-0.119***	0.003
System Design & Engineering (SDE)			**0.060*****	**0.003**	**0.053*****	**0.002**
Machinery Repair & Maintenance (MRM)			**0.019*****	**0.002**	**0.019*****	**0.002**
Welding & Metal Processing (WMP)			-0.003	0.003	-0.001	0.003
Random Effects						
Level-1 variance	0.2016	0.0003	0.2014	0.0003	0.1928	0.0003
Level-2 variance	0.0911	0.0049	0.0907	0.0049	0.0717	0.0040
IRR	0.3112		0.3105		0.2711	
# of observations		825,701		825,701		825,701
Log-likelihood		-512052.80		-511719.35		-493630.58
χ^2 (df)		48944.79 (12)		49652.52 (15)		88929.27 (121)

ROBOTICS SKILLS AND WAGES FOR METRO AREAS

Variables	Base model		Control MSA-level characteristics		Full model	
	Coefficient	Std. Err	Coefficient	Std. Err	Coefficient	Std. Err
Average requirement for years in schooling	0.140***	0.002	0.140***	0.002	0.091***	0.003
Average requirement for job experience	0.081***	0.002	0.080***	0.002	0.052***	0.002
Ratio of Job Ads aligned with SDE	**0.180*****	**0.025**	**0.198*****	**0.026**	**0.160*****	**0.026**
Ratio of Job Ads aligned with MRM	**0.237*****	**0.033**	**0.249*****	**0.033**	**0.119*****	**0.033**
Ratio of Job Ads aligned with WMP	-0.021	0.021	-0.008	0.021	0.002	0.027
# of observations		11,528		11,528		11,528
F-stat (robotic skills)		59.32***		68.73***		21.71***
Adjusted R-squared		0.5814		0.5893		0.7235

Note: *** p<0.01, ** p<0.05, * p<0.1
N = 11,528

ROBOTICS SKILLS AND WAGES FOR METRO AREAS



Basic Model Grid

	Metro Area
Occupation	Ratio of ads aligned with Robotics skills/Median wage advertised

Selected Examples

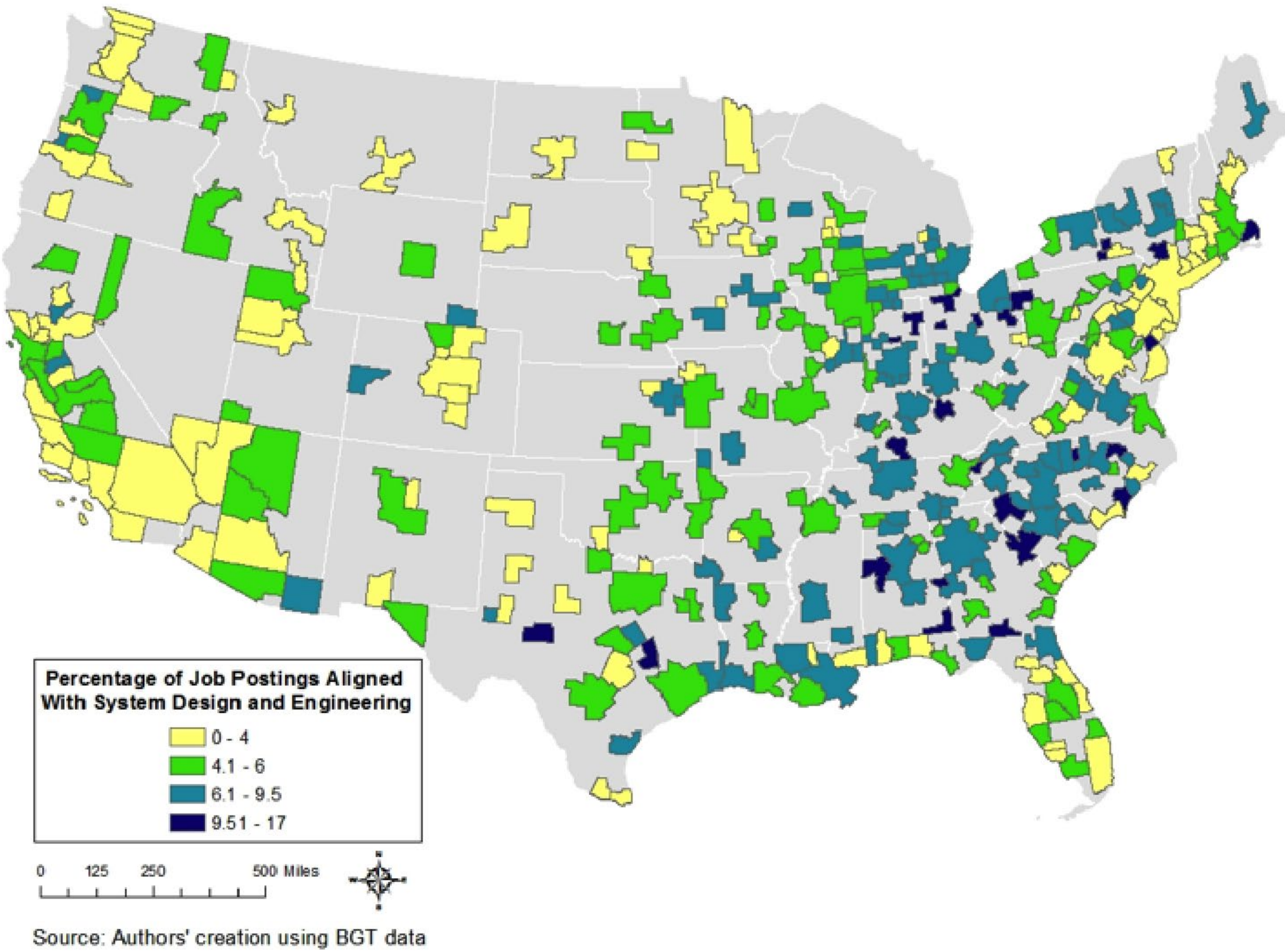
	Portland-Vancouver-Hillsboro, OR-WA
Electrical and Electronic Engineering Technicians	22.4% ads aligned with SDE 19.7% aligned with MRM Median hourly wage = $52

76 jobs advertised

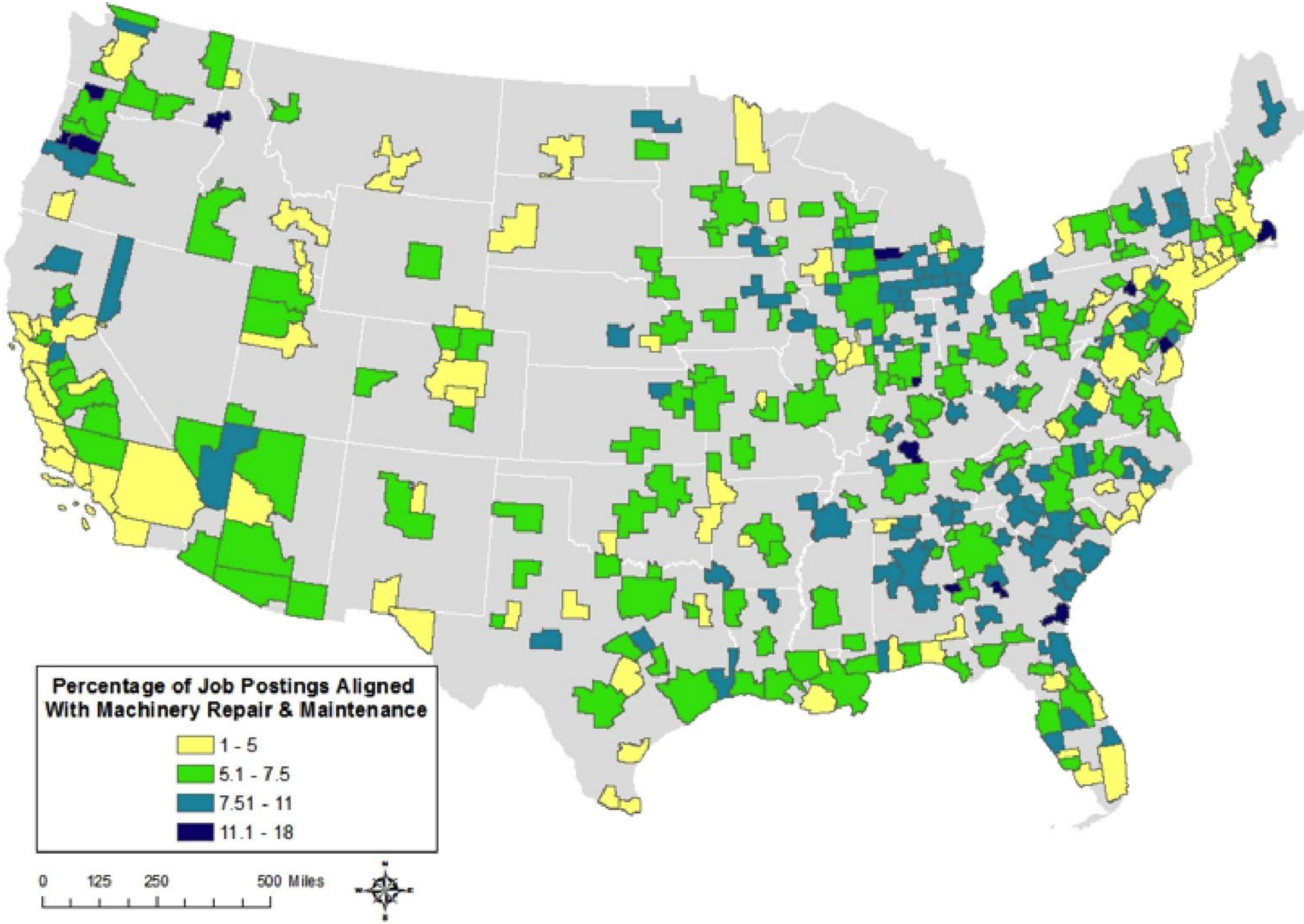
	Seattle-Bellevue-Everett, WA
Electrical and Electronic Engineering Technicians	14.3% ads aligned with SDE 21.4% aligned with MRM Median hourly wage = $42

84 jobs advertised

Percent of manufacturing job postings aligned with Systems Design & Engineering (SDE)

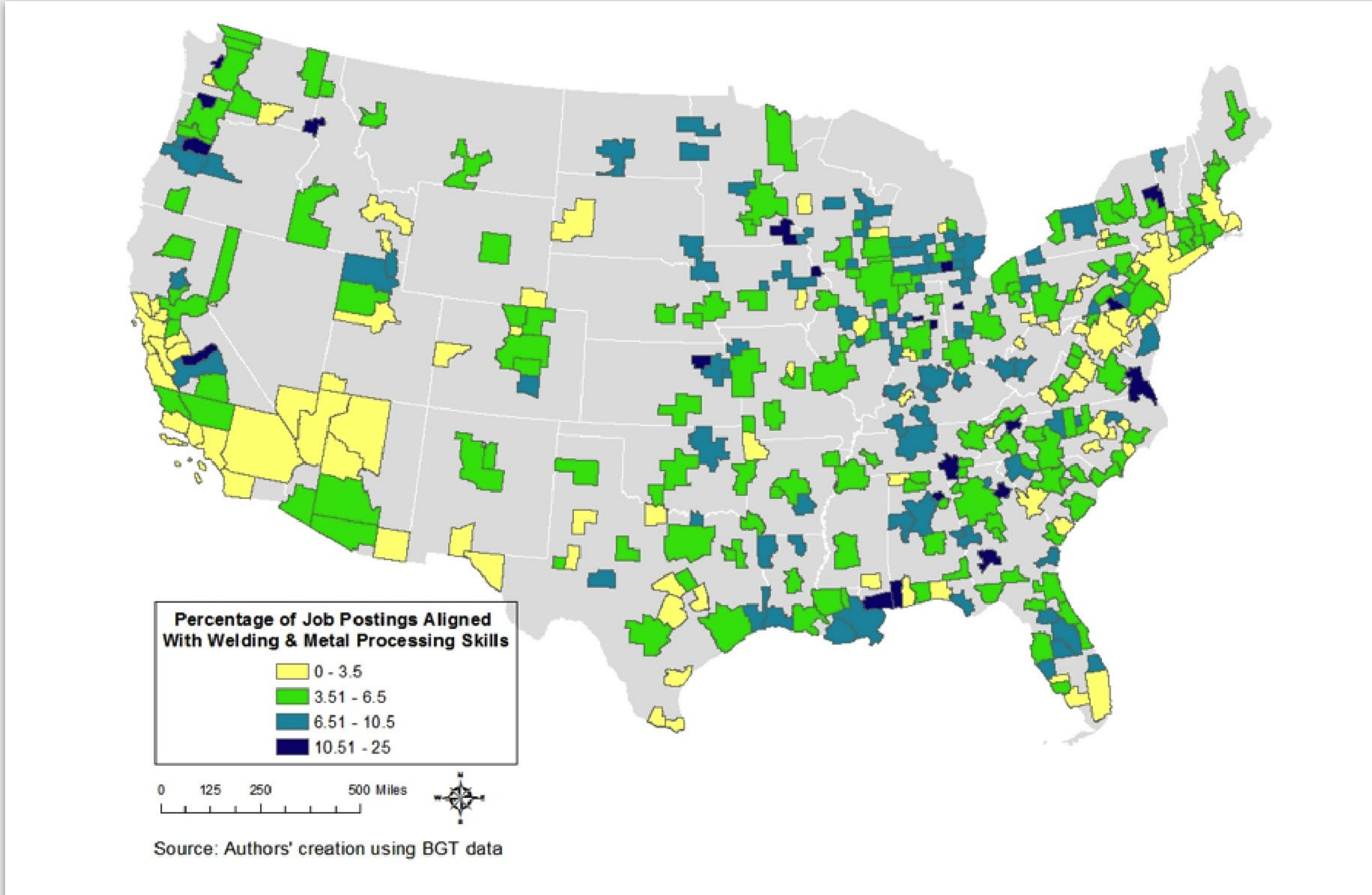


Percent of manufacturing job postings aligned with Machinery Repair & Maintenance (MRM)



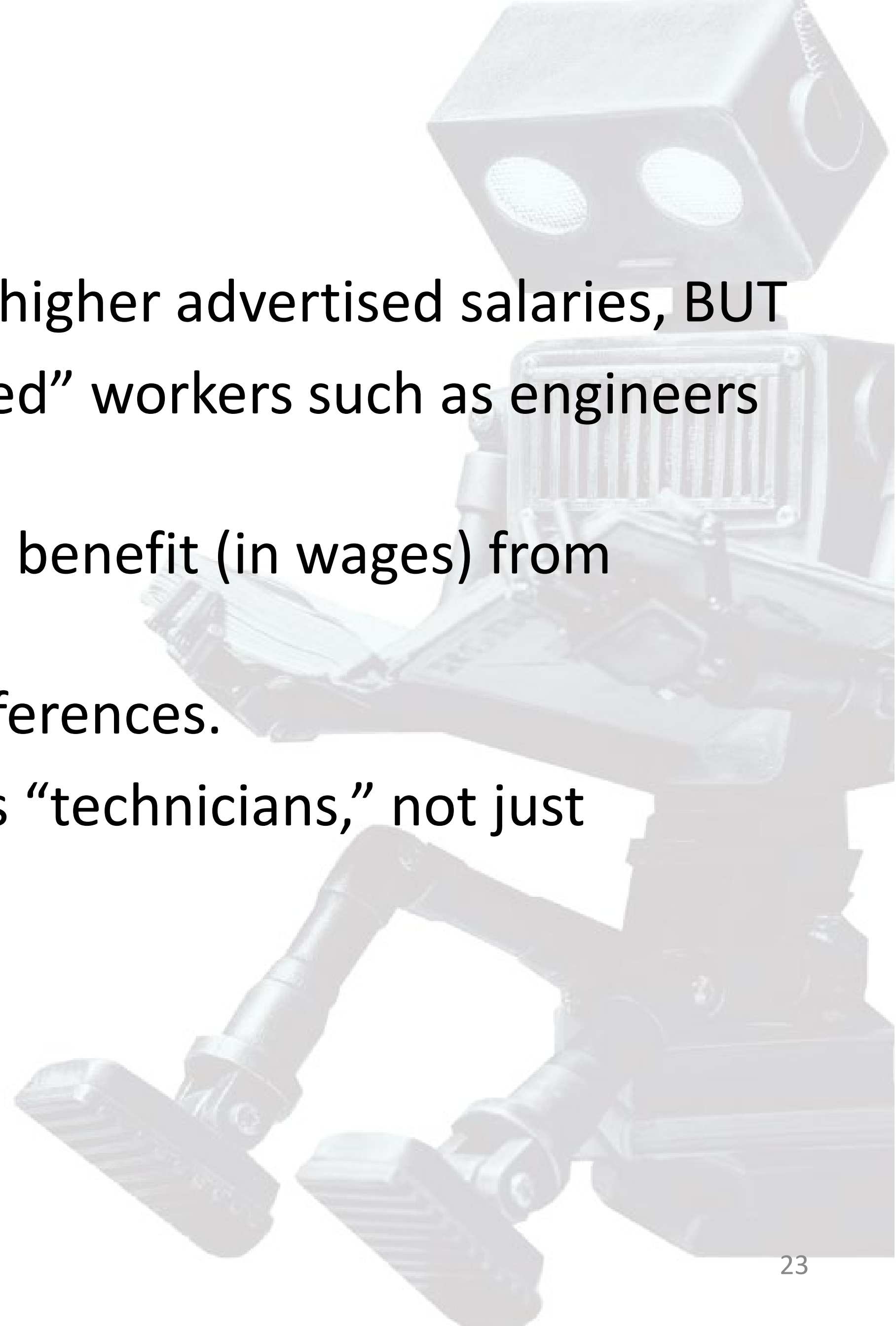
Source: Authors' creation using BGT data

Percent of manufacturing job postings aligned with Welding & Metal Processing (WMP)



MAIN POINTS

- Robotics skills are associated with higher advertised salaries, BUT
- Only for already more “highly skilled” workers such as engineers and technicians.
- Welders and metal workers do not benefit (in wages) from gaining robotics skills.
- There are distinct geographical differences.
- Recommendation: train welders as “technicians,” not just welders.

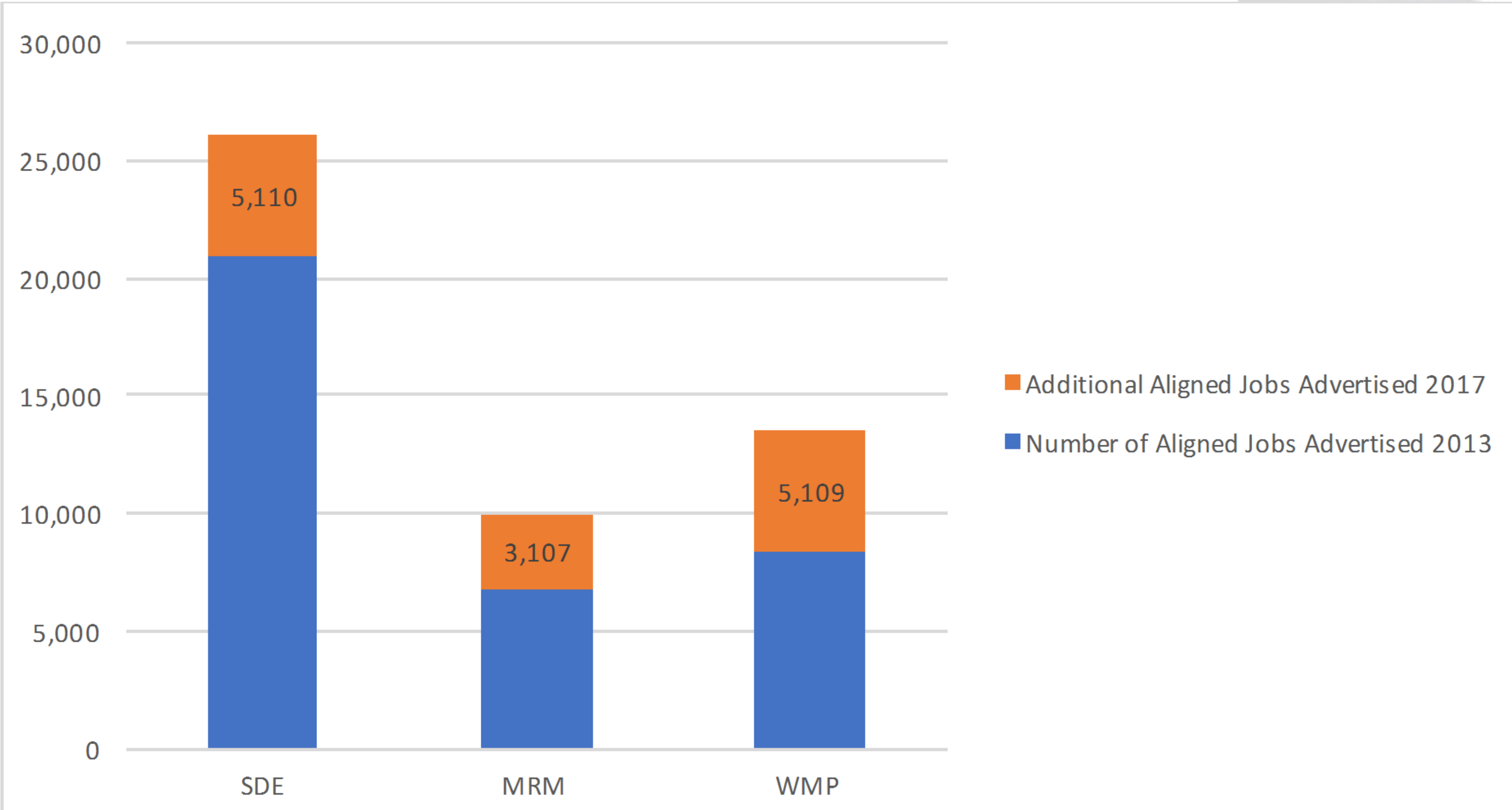


END

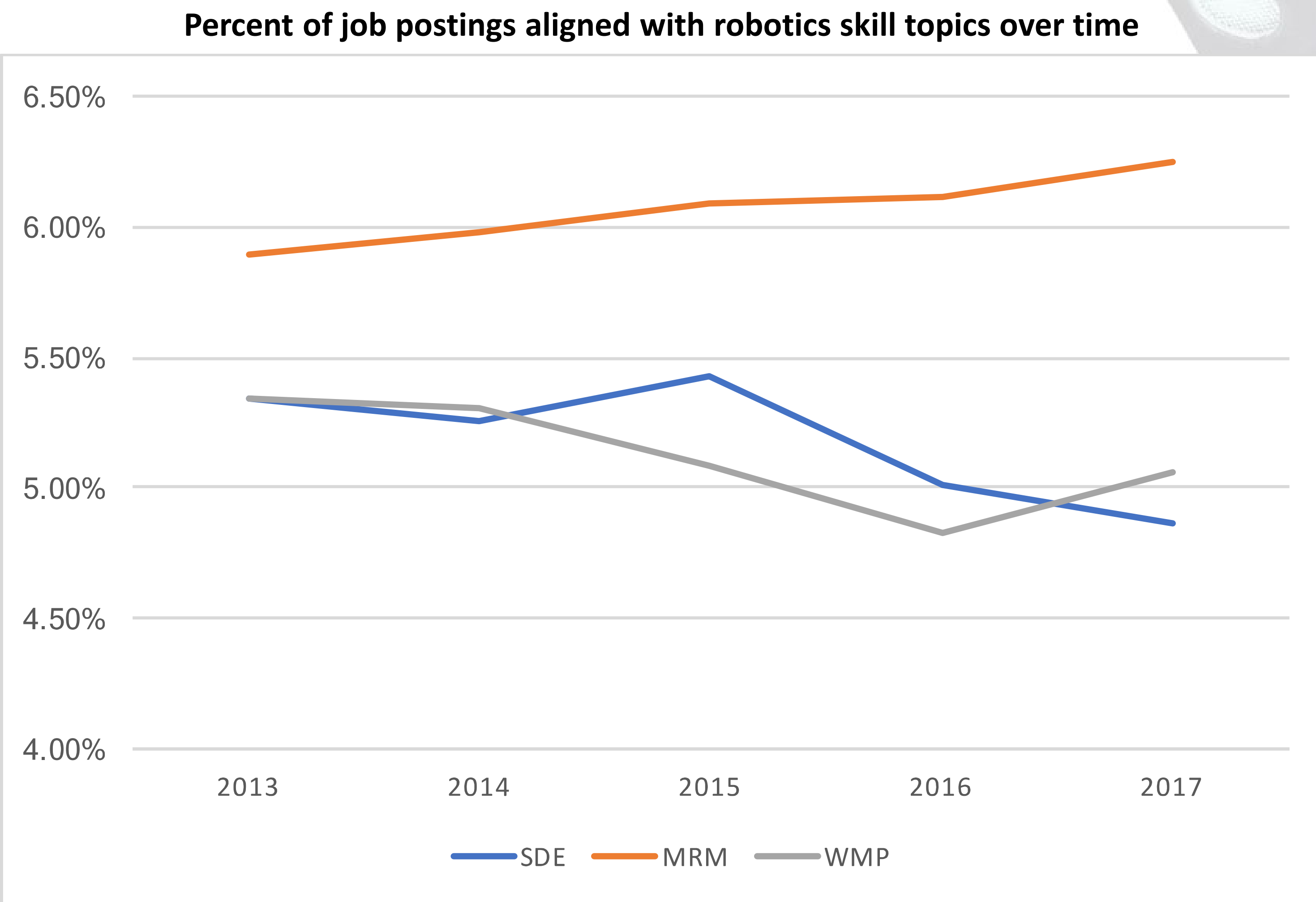
DISCUSSION

EXTRA SLIDES

Number of Job Postings Aligned with Robotics Skill Topics, 2017 compared to 2013



EXTRA SLIDES



EXTRA SLIDES

Descriptive statistics of variables for the wage equation – Individual level

Variable	Mean	Std. Dev.	Min	Min
Log transformed minimum hourly wage	3.074	0.595	1.571	5.482
Degree requirement				
N/A	0.406	0.491	0	1
High school (reference)	0.249	0.432	0	1
Associate	0.037	0.189	0	1
Bachelor's	0.300	0.458	0	1
Master's	0.007	0.081	0	1
Ph.D.	0.002	0.039	0	1
Experience	2.110	2.794	0	15
Experience squared	12.255	29.590	0	225
Part-time dummy	0.042	0.200	0	1
System Design & Engineering (SDE) dummy	0.052	0.221	0	1
Machinery Repair & Maintenance (MRM) dummy	0.061	0.239	0	1
Welding & Metal Processing (WMP) dummy	0.051	0.220	0	1
Posted year				
2013 (reference)	0.133	0.339	0	1
2014	0.145	0.352	0	1
2015	0.239	0.427	0	1
2016	0.248	0.432	0	1
2017	0.235	0.424	0	1
Metropolitan area dummy	0.916	0.278	0	1
Census division dummy				
East North Central (reference)	0.241	0.428	0	1
East South Central	0.061	0.239	0	1
Middle Atlantic	0.102	0.302	0	1
Mountain	0.058	0.233	0	1
New England	0.054	0.226	0	1
Pacific	0.157	0.363	0	1
South Atlantic	0.151	0.358	0	1
West North Central	0.096	0.295	0	1
West South Central	0.080	0.272	0	1

EXTRA SLIDES

Descriptive statistics of variables for the wage equation – MSA-Occupation Level

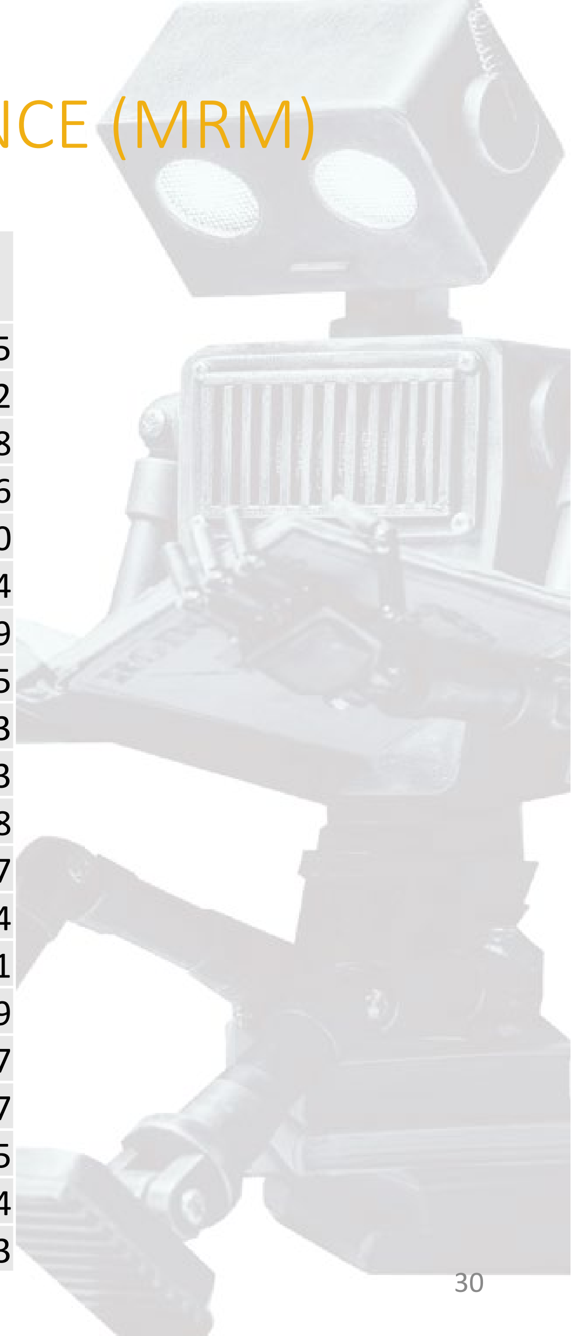
Variable	Mean	Std. Dev.	Min	Min
Log transformed median hourly wage	3.951	0.444	2.796	5.737
Average requirement for years in schooling	13.893	1.687	12.000	21.000
Average requirement for job experience	3.450	1.674	0.080	15.000
Ratio of Job Ads aligned with SDE	0.053	0.117	0.000	1.000
Ratio of Job Ads aligned with MRM	0.063	0.094	0.000	0.917
Ratio of Job Ads aligned with WMP	0.053	0.134	0.000	1.000
Log transformed MSA employment size in 2013	12.926	1.325	9.765	15.942
Log transformed average MSA wage in 2013	10.762	0.198	10.209	11.589
Manufacturing location quotient in 2013	1.218	0.622	0.178	5.122

TOP 20 SYSTEMS DESIGN AND ENGINEERING (SDE)

Metro Area	Total Mfg Jobs	Pct Robotics Aligned WMP
San Angelo, TX	164	16.5
Mansfield, OH	462	15.4
Toledo, OH	2,258	14.5
Rocky Mount, NC	359	13.6
Barnstable Town, MA	198	13.6
Augusta-Richmond County, GA-SC	1,727	12.7
Canton-Massillon, OH	1,062	12.0
Fort Wayne, IN	2,204	11.9
Elmira, NY	237	11.8
Tuscaloosa, AL	589	11.0
Dover, DE	372	11.0
Wilmington, NC	328	11.0
Burlington, NC	430	10.9
Greenville-Anderson-Mauldin, SC	4,821	10.9
Auburn-Opelika, AL	394	10.7
Ithaca, NY	188	10.6
Morristown, TN	397	10.6
Bowling Green, KY	1,069	10.4
Kingston, NY	168	10.1
Youngstown-Warren-Boardman, OH-PA	1,148	10.1

TOP 20 MACHINERY REPAIR & MAINTENANCE (MRM)

Metro Area	Total Mfg Jobs	Pct Robotics Aligned MRM
Corvallis, OR	206	17.5
Lewiston, ID-WA	125	15.2
Longview, WA	250	14.8
Gary, IN	1,029	14.6
Auburn-Opelika, AL	394	14.0
Albany, OR	336	13.4
Bowling Green, KY	1,069	12.9
Bloomsburg-Berwick, PA	112	12.5
Muskegon, MI	635	12.3
Brunswick, GA	163	12.3
Dover, DE	372	11.8
Warner Robins, GA	171	11.7
Columbus, IN	780	11.4
Barnstable Town, MA	198	11.1
Erie, PA	850	10.9
Dutchess County-Putnam County, NY	289	10.7
Burlington, NC	430	10.7
Clarksville, TN-KY	617	10.5
San Angelo, TX	164	10.4
Muncie, IN	330	10.3



TOP 20 WELDING & METAL PROCESSING (WMP)

Metro Area	Total Mfg Ads	Pct Robotics Aligned WMP
Longview, WA	250	24.8
Gulfport-Biloxi-Pascagoula, MS	405	22.7
Manhattan, KS	207	22.7
Rochester, MN	877	16.6
Albany, OR	336	14.6
Athens-Clarke County, GA	813	14.3
Gary, IN	1,029	14.0
Lewiston, ID-WA	125	13.6
Gadsden, AL	170	13.5
Muncie, IN	330	12.7
Mobile, AL	1,204	12.7
Kokomo, IN	187	12.3
Lima, OH	608	11.7
Glens Falls, NY	155	11.6
Johnson City, TN	422	11.6
Albany, GA	181	11.6
Madera, CA	113	11.5
Dubuque, IA	1,141	11.2
Virginia Beach-Norfolk-Newport News, VA-NC	2,994	11.0
Bremerton-Silverdale, WA	323	10.8