

# Corporate Governance, Ownership, and the Introduction of New Technology

Adrianto and Avner Ben-Ner

Carlson School of Management, University of Minnesota,

Kelso Workshop

Rutgers Institute for Employee Ownership and Profit Sharing



# Ownership and new technologies Scope and questions



#### Ownership

- Employee-owned Firms (ESOPs)
- Conventional Firms (CFs)

(Also publicly traded-privately held)

### **New technologies**

- Robots (industrial)
- AI and ML

### **Questions-comparisons by ownership**

- 1. Penetration prevalence
- 2. Propensity to adopt timing
- 3. Effect of adoption
  - a. Demand for labor
  - b. Workplace safety

### Data

- Job postings Manufacturing 2010-22
- Employment 2016-22
- Workplace safety 2016-22



AI-ML

### **Industrial Robots**







# Background on Effects of Robot and AI-ML Theory and evidence in the literature



### **Industrial robots**

- Increase plant productivity
- Substitute some low skill worker tasks
- Complement labor
- Low and high skill workers complement robots
- Net effect on demand for labor
- Theoretically ~indeterminate
- Empirically positive for all skills
- Literature review and evidence
- Adrianto, Ben-Ner & Urtasum, "Robots and Work" 2024

Probably Similar effects to robots

AI-ML

But too early to tell; literature finds many contingencies



# **Presentation today**



- A. Penetration prevalence 2022 (logit)
- B. Propensity to adopt timing 2010-2022 (Cox proportional hazards)
- C. Introduction of ESOP and adoption of new technology (DiD)
- D. Effect of adoption
  - 1. Demand for labor (DiD)
  - 2. Workplace safety (DiD)



# Theoretical framework ESOP-CF differences in technology adoption

### **ESOPs relative to CFs**

- Internalize both profitability and employment effects
- Greater information sharing (up and down) and participatory decision-making
- Time horizons longer
- Incentive alignment among workers of different occupations/skills as well as low and middle managers

 More careful evaluation of technology adoption

Therefore:

- Emphasis on worker-technology complementarity
- Ambiguous predictions



# **Findings summary**



- A. Penetration prevalence: Higher in ESOPs
- B. Propensity to introduce-adopt Faster in ESOPs
- C. Introduction of ESOP and adoption of new technology: positive, confirms A and B
- D. Effect of adoption
  - 1. Demand for labor: increases more for ESOPs than for CFs
  - 2. Workplace safety: reduction same in ESOPs and CFs



# Data



### Datasets

- Job postings BGT
- Injuries OSHA
- ESOPs NCEO and DoL/IRS Form 5500
- COMPUSTAT

Plant and firm level data

- Firm level ownership variable
- Plant level adoption of technology
- Plant level demand for labor and injuries

Related work with these datasets (on my homepage)

- Adrianto, Avner Ben-Ner, and Ainhoa Urtasun, Robots and Work, 2024
- Adrianto, Avner Ben-Ner, Jason Sockin, and Ainhoa Urtasun, Sharing is Caring: Employee Stock Ownership Plans and Employee Satisfaction in U.S. Manufacturing, 2024



# Identification of technology adoption



1. Technology adoption: At least one term included in ten production job postings

2. Timing of introduction: First time a technology posting appears (Robustness checks)

Technology	Terms used (job postings)
AIML	machine learning (132,375), artificial intelligence (77,626), deep learning (34,783), computer vision (22,231), neural networks (15,108), decision trees (7,872), keras (7,199), opencv (5,337), random forests (3,395), support vector machines (svm) (3,082), ibm watson (1,988), mxnet (1,438), mahout (1,343), recommender systems (1,272), object tracking (671), xgboost (580), gradient boosting (578), h2o (software) (472), virtual agents (364), ipsoft amelia (141), ai chatbot (119), deeplearning4j (54), madlib (26), libsvm (19), ithink (18), pybrain (15), microsoft cognitive toolkit (12), mlpack (c++ library) (7), google cloud machine learning platform (2), mlpy (2) <i>(Erom BGT AL and ML skill clusters</i> )
Robotics	robotics (198,415), robotic systems (13,392), robot programming (6,721), robot operating system (ros) (4,095), robot framework (1,297), advanced robotics (434), robotic liquid handling (373), motoman robot programming (222), pick and place robots (162), next generation robotics (71)



# **Descriptive statistics**





### A. Penetration rate of Robotic and AIML by ownership Percentage of plants with Robotic and AIML



Robotic







### **B. Adoption rate of Robotic and AIML by ownership** New adopters as a share of total plants

Robotic



UNIVERSITY OF MINNESOTA



# Penetration and adoption rates **Public firms only**





### Descriptive statistics End of 2022



	A 11	CE	ECOD	Non-CBA	CBA
	All	CF	ESOP	ESOP	ESOP
Firms	94,015	93,040	975	913	62
Plants	372,726	341,735	30,991	22,230	8,761
Plants/firm	3.96	3.67	31.8	24.3	141
Postings	14,178,031	10,348,460	3,829,571	2,264,227	1,565,344
Postings/plant	38	30.3	124	102	179
High-skill postings/plant	11.1	7.76	48.4	36.2	79.3
Low-skill postings/plant	5.97	5.29	13.4	11.4	18.4
Public firms (%)	3.39	3.25	17	13	75.8
Robotic plants (%)	0.581	0.456	1.96	1.65	2.75
AIML plants (%)	0.69	0.539	2.35	1.71	3.98
Reporting injuries to OSHA (%)	9.14	9.15	9.02	8.96	9.17
Injuries/1 million work hours	15.6	16	12	13.6	8.16
	ESOP c	haracteristics			
Mean ESOP age			21.9	20.7	39
Total participants/firm			5,199	3,667	27,621
Active participants/firm			3,635	2,698	17,563
Plan assets/total participant			150,130	147,839	183,862
Plan assets/active participant			197,910	192,438	278,494
Plan assets/firm equity (for public firms)			0.16	-0.154	0.951
Plan assets/firm assets (for public firms)			0.268	0.272	0.257



# Analyses



# A. Technology penetration rate 2022, ESOP vs. CF (logit)

 A1. ESOP sample only: CBA vs. non-CBA A2. ESOP sample only: ESOP assets/participant A3. Public ESOP sample only: ESOP assets/firm

### B. Technology introduction 2011-2022 (proportional hazards)

- B1. ESOP sample: ESOP assets/participant
- B2. ESOP sample: ESOP assets/firm equity

# C. Effect of *ESOP adoption* in *t* on technology adoption in t to t+4 (DiD)

# D1. Effects of technology adoption on job postings – ESOP vs. CF (DiD)

- Comparisons
  - ESOP adopters vs. CF adopters
  - ESOP adopters vs. ESOP nonadopters
  - CF adopters vs. CF non-adopters
  - ESOP CBA vs. non-CBA

D2. Effects of technology adoption on injury rates – ESOP vs. CF (DiD)

D3. Effects on employment



### A. Technology penetration and ownership, 2022 (Logit)



	Robotic		AI	ML	Robotic+AIML		
	(1)	(2)	(3)	(4)	(5)	(6)	
1(ESOP)	1.069***	0.728***	0.945***	0.340	1.285***	0.806***	
	(0.160)	(0.181)	(0.245)	(0.314)	(0.259)	(0.269)	
Size <sup>(1)</sup>	0.013***	0.006***	0.024***	0.019***	0.013***	0.013***	
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	
1(Public)	-	0.381***	-	1.384***	-	1.181***	
		(0.144)		(0.362)		(0.239)	
1(AIML)	-	3.458***	-	-	-	-	
		(0.201)					
1(Robotics)	-	-	-	3.284***	-	-	
				(0.186)			
Fixed effects:							
3-digit NAICS	Yes	Yes	Yes	Yes	Yes	Yes	
Commuting zone							
dummy	Yes	Yes	Yes	Yes	Yes	Yes	
Observations <sup>(2)</sup>	348,098	348,098	339,735	339,735	277,245	277,245	
R <sup>2</sup>	0.0426	0.0986	0.13	0.189	0.0906	0.0961	
Pseudo R <sup>2</sup>	0.126	0.201	0.259	0.339	0.252	0.266	

Notes:

(1) Proxy for size: Job postings in the year when a plant enters the sample.

(2) Plants missing address could not be matched with a CZ were dropped. Odds ratio calculation:  $2.71 \times 1.069 = 2.91$ . 2.91 - 1 = 1.9, which means

ESOP has a 190% greater probability than CF to adopt robots



### A. Technology penetration Effect of of ESOP stakes (in ESOP sample) Summary of results



	Robotic		AIML		Robotic-AIML	
-	(1)	(2)	(3)	(4)	(5)	(6)
ESOP assets/participant	1.398**	0.987*	3.152***	3.187***	2.831***	3.001***
(in millions)	(0.567)	(0.558)	(0.885)	(0.845)	(0.722)	(0.762)
ESOP assets to firm	0.093*	0.101	0.022	-0.002	0.101*	0.101*
equity	(0.051)	(0.075)	(0.053)	(0.064)	(0.057)	(0.057)
1(CBA)	0.302	0.010	0.748*	0.751*	0.256	0.188
	(0.266)	(0.277)	(0.392)	(0.447)	(0.318)	(0.313)

Notes: Each row shows coefficients from a separate logit model. Data is cross-sectional. Control variables include first-year postings, an indicator of whether the firm is publicly traded, an indicator of whether the other technology is adopted in the same firm before the main technology is adopted, 3-digit NAICS fixed effects, and commuting zone fixed effects.



### B. Propensity of technology introduction/adoption by ownership Discrete-time hazard model, all plants

	Rob	otic	AII	ML
	(1)	(2)	(3)	(4)
1(ESOP)	0.914***	0.457**	0.876***	0.226
	(0.175)	(0.196)	(0.260)	(0.316)
First-year postings	0.004***	0.002***	0.007***	0.005***
	(0.001)	(0.000)	(0.001)	(0.001)
1(Public)	-	0.525***	-	1.406***
		(0.148)		(0.381)
1(AIML)	-	3.607***	-	-
		(0.168)		
1(Robotic)	-	-	-	3.029***
				(0.223)
Fixed effects:				
3-digit NAICS	Yes	Yes	Yes	Yes
Commuting zone	Yes	Yes	Yes	Yes
Observations	2,846,187	2,846,187	2,814,632	2,814,632
R <sup>2</sup>	0.000619	0.0082	0.00305	0.014
Pseudo R <sup>2</sup>	0.0599	0.111	0.134	0.196

Notes: Table show results from logit regressions on the marginal propensity of technology adoption in ESOP. The data is longitudinal. Post-adoption data are removed, leaving the adoption year as the last observation year for an adopting plant.

UNIVERSITY OF MINNESOTA

CARLSON

# Marginal propensity of technology adoption in ESOP v CF

log odds of new technology adoption by ownership and year. Control

#### **Robotic**

AIML



Notes: Figures show the predicted log odds of new technology adoption by ownership and year. Control variables include first-year postings, an indicator of whether the firm is publicly traded, an indicator of whether the other technology is adopted in the same firm before the main technology is adopted, 3-digit NAICS fixed effects, and commuting zone fixed effects.



# Cumulative penetration of technology by ownership Discrete-time hazard model, all establishments



## Robotic



AIML

Notes: Figures show the predicted log odds of (cumulative) technology penetration by ownership and year. Control variables include first-year postings, an indicator of whether the firm is publicly traded, an indicator of whether the other technology is adopted in the same firm before the main technology is adopted, 3-digit NAICS fixed effects, and commuting zone fixed effects.



### B. Technology introduction Effect of of ESOP stakes (in ESOP sample) Summary of results



	Robotic			AIML		
	(1)	(2)	-	(3)	(4)	
ESOP assets/participant	1.252***	1.367***		1.893***	2.194***	
(in millions)	(0.326)	(0.351)		(0.409)	(0.409)	
ESOP assets to firm						
equity	0.073*	0.097*		-0.009	-0.018	
	(0.043)	(0.050)		(0.061)	(0.063)	



## C. Effect of ESOP adoption in year t on technology adoption in t, t+1, t+2, t+3, and t+4 (DiD)

DiD (Callaway-Sant'Anna) with PSM on NAICS, CZ, and size

- Treatment: Introduction of ESOP
- Outcome: adoption of robots/AIML

Technology	Preadoption mean	ATT
(1) Robotic	0.013	0.006** (0.00)
(2) AIML	0.005	0.007** (0.00)
Treated plants		922
Untreated plants		1,202,517

 Note: Preadoption value is calculated as the share of robotic ESOP plants among all ESOP plants in 4 years before a CF adopts ESOP



UNIVERSITY OF MINNESOTA

# D, Effects of technology adoption on job postings – ESOP vs. CF



- DiD (Callaway & Sant'Anna)
- Outcome variable: change in job postings/employment/injuries
- PSM by NAICS, CZ labor cost and availability, Size, Public/Private
- Treatment: robot (AI-ML) introduction
- Comparisons
  - ESOP adopters vs. CF adopters
  - ESOP adopters vs. ESOP non-adopters
  - CF adopters vs. CF non-adopters
  - ESOP CBA vs. non-CBA



### D1. Technology adoption effect on change in job postings ESOP adopter vs. CF adopter (DiD)



	Average	e Effect	by Leng	th of Ex	posure					
150-	A	IML			÷	Ī	Ī	Ī		
100-									-	
50-										
0-										
	-4	-3	-2	-1	ò	1	2	ż	4	
				+	Pre 🔸	Post				

Technology (as treatment)	Preadoption mean	ATT	Treated	Untreated
(1) Robotic	89.90	79.63*** (11.23)	473	1,188
(2) AIML	110.33	87.30*** (22.62)	692	1,706

\* Covariates include 3-digit NAICS, first-year postings, CZ log of wage, CZ population of working age, and an indicator of whether the firm is publicly listed.



### D2. Event study analysis of change in *injuries/1m* work hours ESOP adopter vs. CF adopter (Did)

Robotic



\* Covariates include 3-digit NAICS, first-year employment, CZ log of wage, CZ population of working age, and an indicator of whether the fire



# Effect on job postings (left) & injuries per 1M work hours (right) – various comparisons



Technology (as treatment)	Preadoption mean	ATT	Treated	Untreated	Technology (as treatment)	Preadoption mean	ATT	Treated	Untreated
(1) Robotic	89.90	129.98*** (4.90)	473	95,511	(1) Robotic	6.756	2.347** (1.183)	36	3,289
(2) AIML	110.33	227.71*** (2.82)	692	95,372	(2) AIML	4.058	0.701 (1.311)	40	3,311

#### CBA ESOP adopter:Non-CBA ESOP adopter

Technology (as treatment)	Preadoption mean	ATT	Treated	Untreated	Technology (as treatment)	Preadoption mean	ATT	Treated	Untreated
(1) Robotic	93.70	46.95 (30.59)	193	280	(1) Robotic	5.177	-1.801 (1.769)	11	25
(2) AIML	102.87	9.77 (55.68)	338	354	(2) AIML	6.454	1.780 (3.472)	10	30

Notes: Each row shows coefficients from a separate DiD model. Treated and untreated units are matched using 3-digit NAICS, log of wage in a commuting zone in 2007, population of working age in a commuting zone in 2007, plant first-year postings, and an indicator of whether the firm is publicly traded.



# **Findings summary**



- A. Penetration prevalence: Higher in ESOPs
- B. Propensity to adopt Faster in ESOPs
- C. Introduction of ESOP and adoption of new technology: positive, confirms A and B
- D. Effect of adoption
  - 1. Demand for labor: increases more for ESOPs than for CFs
  - 2. Workplace safety: reduction same in ESOPs and CFs



# Thanks!







# **APPENDIX**



# Effect on employment (left) & log of employment (right) – various comparisons



ESOP adopter: ESOP non-adopte	r
-------------------------------	---

Technology (as treatment)	Preadoption mean	ATT	Treated	Untreated	Technology (as treatment)	Preadoption mean	ATT	Treated	Untreated
(1) Robotic	640.973	-24.871 (70.540)	36	3,289	(1) Robotic	5.975	0.026 (0.106)	36	3,289
(2) AIML	788.404	236.795** (109.916)	40	3,311	(2) AIML	6.138	0.256 (0.263)	40	3,311

#### CBA ESOP adopter:Non-CBA ESOP adopter

Technology (as treatment)	Preadoption mean	ATT	Treated	Untreated		Technology (as treatment)	Preadoption mean	ATT	Treated	Untreated
(1) Robotic	360.929	783.384** (305.207)	11	25	_	(1) Robotic	5.607	1.284*** (0.380)	11	25
(2) AIML	374.072	332.672** (138.256)	10	30	_	(2) AIML	5.134	0.426 (0.430)	10	30

Notes: Each row shows coefficients from a separate DiD model. Treated and untreated units are matched using 3-digit NAICS, log of wage in a commuting zone in 2007, population of working age in a commuting zone in 2007, plant first-year postings, and an indicator of whether the firm is publicly traded.



### Propensity of new technology adoption by ownership Discrete-time hazard model, within public ESOP

	Rob	otic	AIN	ЛГ
	(1)	(2)	(3)	(4)
Plan assets to firm equity	0.073*	0.097*	-0.009	-0.018
	(0.043)	(0.050)	(0.061)	(0.063)
First-year postings	0.006***	0.002***	0.008***	0.006***
-	(0.001)	(0.001)	(0.001)	(0.001)
1(AIML)	-	3.929***	-	-
		(0.307)		
1(Robotic)	-	-	-	3.164***
				(0.238)
Fixed effects:				
3-digit NAICS	Yes	Yes	Yes	Yes
Commuting zone	Yes	Yes	Yes	Yes
Observations	205,897	205,897	203,814	203,814
R <sup>2</sup>	0.00449	0.0262	0.0141	0.0362
Pseudo R <sup>2</sup>	0.0304	0.109	0.0944	0.147

Notes: Table show results from logit regressions on plan assets to firm equity. Sample include all public ESOP firms. Data is longitudinal. Post-adoption data are removed, leaving the adoption year as the last observation year for an adopting plant.



