

Technology and the Size and Composition of Workforce in U.S. Firms: First Evidence from the 2019 Annual Business Survey

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Outline

- Overview of the 2019 Annual Business Survey
- Firm Adoption of Technologies
- Motivation and Adverse Factors for Adoption
- Employment Outcomes from Adoption
 - Worker Types (Production Workers (PW), Non-Production (NP), Supervisory Workers (SW) and Non-Supervisory (NSW))
 - Skills
 - Automation



Preview of Findings

Technology Adoption

- Specialized software and cloud computing are most adopted and Robotics and AI are least adopted
- Adoption driven by sector and skewed towards largest and oldest firms
 - Worker exposure to technology is significantly higher

Motivations/ Adverse Factors for Adoption

- Quality improvement and upgrading production are most common
- Automation is a major motivator for AI and robotics
 - Large share of manufacturing workers exposed to automation via technology
- Cost is a key adverse factor; AI and robotics often cited as “immature”

Employment Outcomes

- Most respondents report no employment change attributable to tech
- Employment increases more likely attributed to AI
- Employment decreases more likely attributed to robotics -> production workers most impacted
- Large share of firms report skill upgrading attributed to tech

Overview of the Annual Business Survey (ABS)

- Background

- Enterprise-level survey first conducted in 2018
- Joint with NSF/National Center for Science and Engineering Statistics
- Mailed to 300,000 nationally representative employer businesses
 - Approximately 208,000 linked responses
 - Represents 6.1M firms and 140M+ employees
- Combines three pre-existing enterprise-level surveys: Survey of Business Owners (SBO), Annual Survey of Entrepreneurs (ASE), Business R&D and Innovation Survey for Microbusiness (BRDI-M)

Weighting &
Summary Stats

- New business topic modules introduced each year, including:

- 2019 ABS (reference year 2018) focuses on adoption and workforce impacts of AI, cloud services, specialized software, robotics, and specialized equipment
- 2018 ABS (reference year 2017) focuses on the adoption and use of digitization, cloud services, and advanced business technologies

2018 ABS
Comparison

Technology Adoption by Firms

- Two types of technology deployments
 1. Technology *used* in **production processes** (of goods and services)
 2. Technology *sold* in **goods and services** themselves (less common)
- Adoption is closely associated with **size** and **productivity**
- Most adopted technologies (Equipment, Cloud, and Software) are also most intensively adopted
- Nearly 60% of firms adopt zero technologies; firms adopting at least one technology are more likely to adopt a technology pair

Size/Age
Heat Maps

Response &
Intensity

of Techs
Used

Technology Usage Rates (%)

	Weighting	AI	Cloud Comp.	Spec. Equip.	Robotics	Spec. Soft.
Processes & Methods	Firm	3.2	34.0	19.5	2.0	40.1
	Employment	12.5	61.5	36.3	15.7	64.1
Goods & Services	Firm	0.5	3.5	2.5	0.3	4.3
	Employment	2.2	7.1	4.8	1.8	7.7

Note: Usage rates drop Missing and "Don't Know"

Technology Adoption by Sector

- AI, cloud, and software most adopted in Information and Professional Services sectors
- Robotics and equipment are most adopted in Manufacturing

Firm-weighted

	AI (%)	Cloud (%)	Specialized Equipment (%)	Robotics (%)	Specialized Software (%)
Agriculture,..., Mining, Utilities	21.4	66.0	49.3	25.6	68.3
Construction	4.3	48.6	34.0	6.7	51.5
Manufacturing	22.6	62.3	70.7	45.1	72.3
Wholesale Trade	16.1	61.1	47.3	22.0	65.3
Retail Trade	15.0	61.1	39.6	16.7	58.4
Transportation & Warehousing	25.7	69.7	49.7	22.7	73.6
Information	29.4	81.0	51.1	11.6	80.0
Finance, Insurance, Real Estate	17.4	72.2	13.5	12.0	74.1
Professional Services	21.0	72.3	32.1	17.3	74.2
Management & Administrative	5.6	58.5	15.7	2.5	62.5
Education	5.4	72.3	25.1	2.9	64.8
Health Care	12.9	66.5	44.4	23.5	70.2
Other (Arts, Food, Other)	4.0	46.0	25.5	5.4	52.0

4-digit NAICS

Note: Employment-weighted. Usage rates drop Missing and "Don't Know"

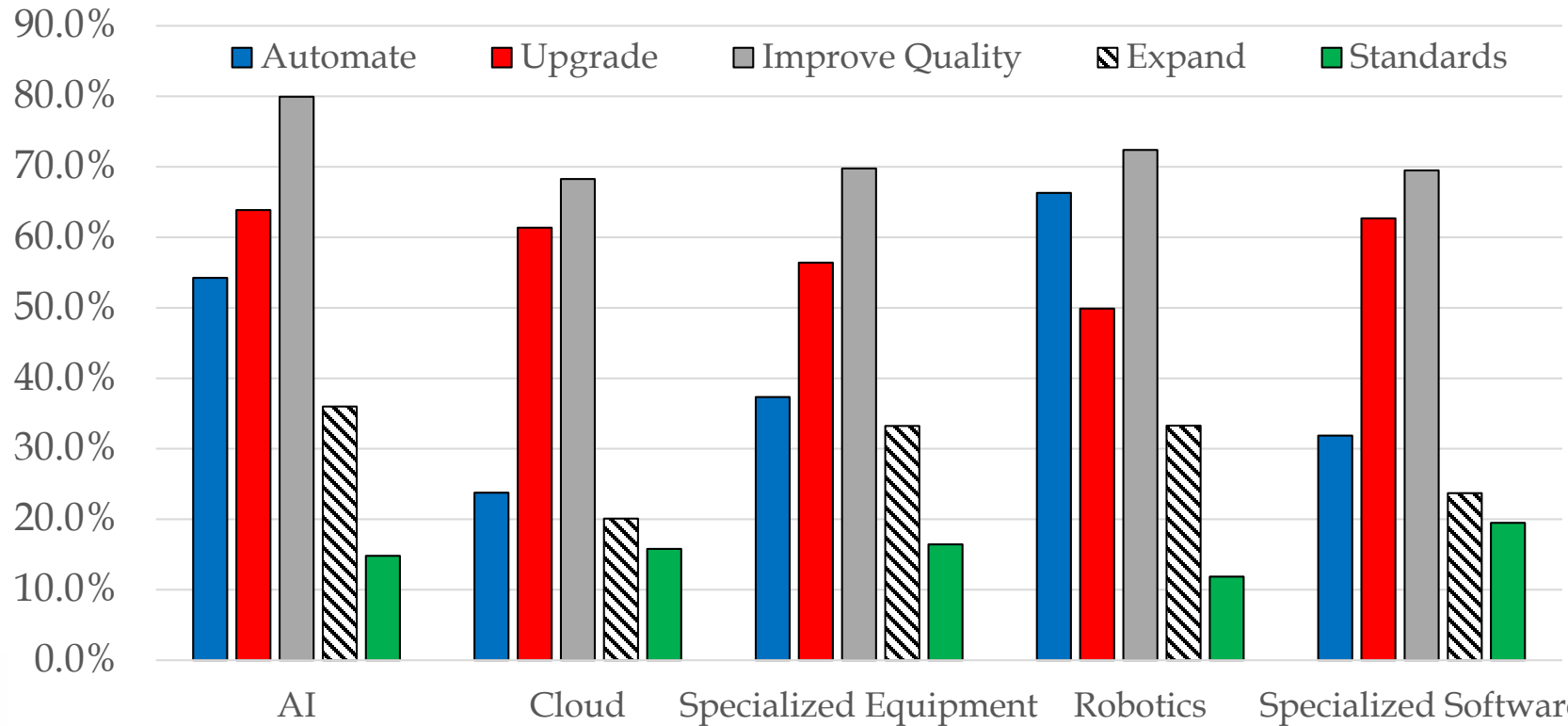
Motivation for Technology Adoption

- Improving Quality and Upgrading* are the two leading motivators for the majority of adopting firms, except those that adopt Robotics
- AI & Robotics adoption more likely motivated by Automation
 - Firm size positively linked with automation, upgrading production and improving quality

Firm-weighted

Size and Age

Manufacturing Status



*Note: Here “upgrading” and “improving quality” refer to the upgrading or improving quality of **processes or methods**, not necessarily the upgrading or improving quality of the goods or services themselves. These are weighted by Employment.

Worker Exposure to Automation

- Differences in automation driven by size and sector
 - Largest differences occur in AI and Robotics
- Despite relatively small adoption rates, 10.4% of workers are exposed to automation via Robotics
 - More than 37% of manufacturing workers are exposed to automation via Robotics

Firm-weighted

Worker Exposure to Automation by Technology (%)`

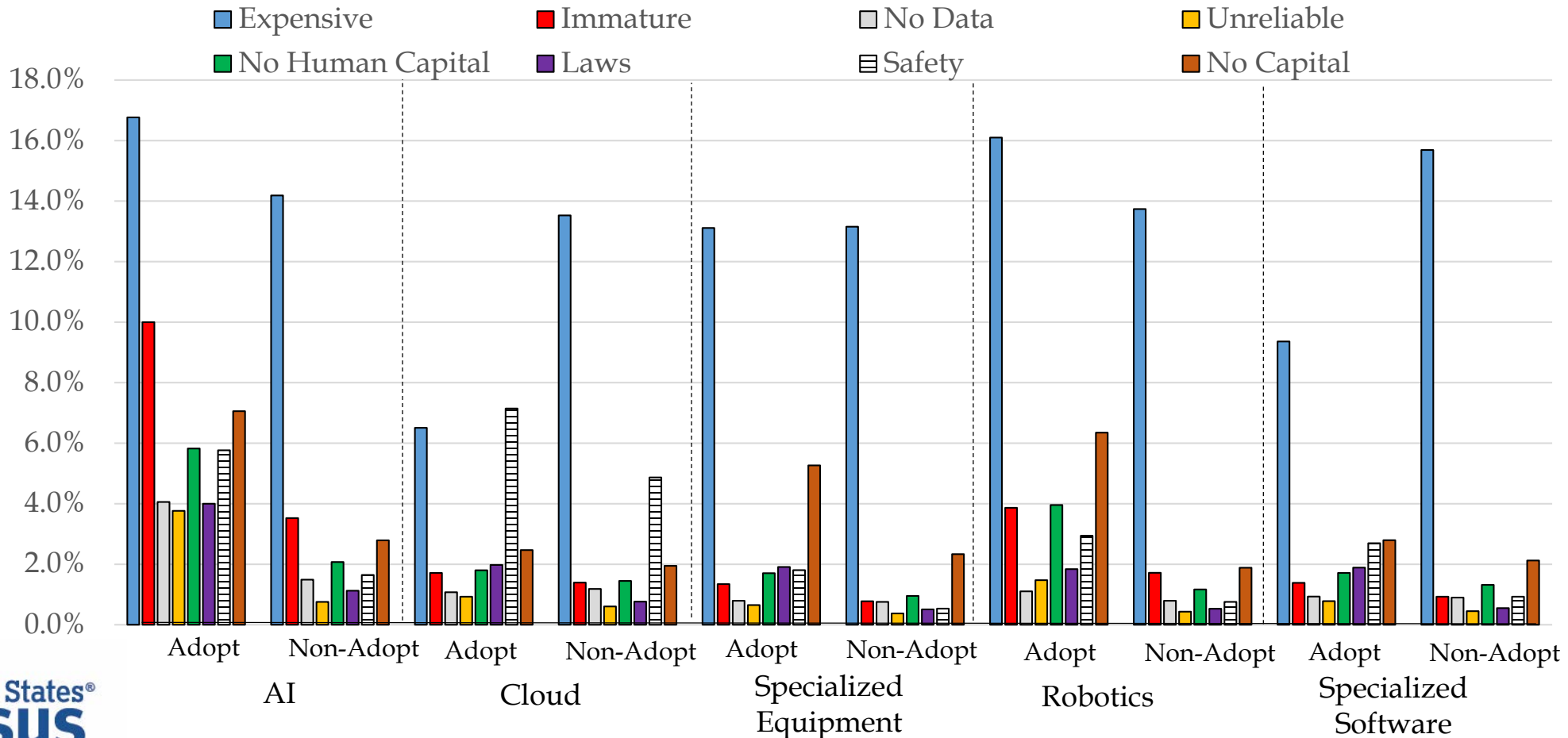
Type	AI	Cloud Comp.	Spec. Equip.	Robotics	Spec. Soft.
All	6.8	14.6	13.6	10.4	20.4
Manufacturing	17.6	18.8	37.8	37.6	29.8

Adverse Factors for Technology Adoption

- Cost is biggest adverse factor for adoption other than inapplicability (not shown)
- AI and Robotics are still considered relatively immature
- Businesses are concerned about safety/security of cloud services

Employment-weighted

NA and No Adverse Factors

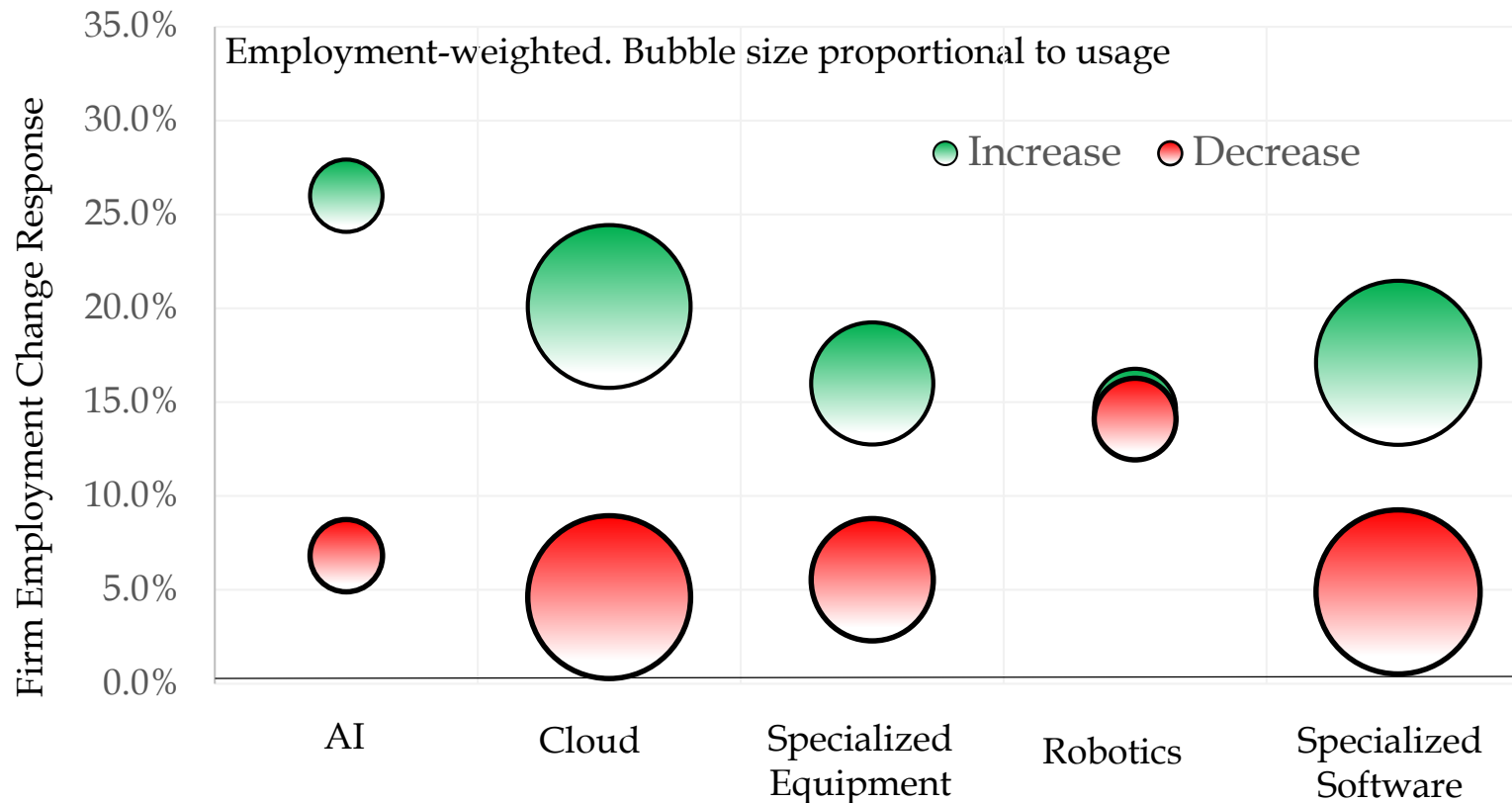


*Conditional on technology being applicable. "No adverse factors" category is dropped in figure.

Employment Changes Attributed to Tech

- Majority of adopters do not attribute employment change to tech (~70%)
 - Self-reported - Need to validate using longitudinal Census data
- More firms attribute employment increases to tech than decreases
- More firms on net attribute employment increases to tech
 - Robotics has smallest net difference

Firm-weighted

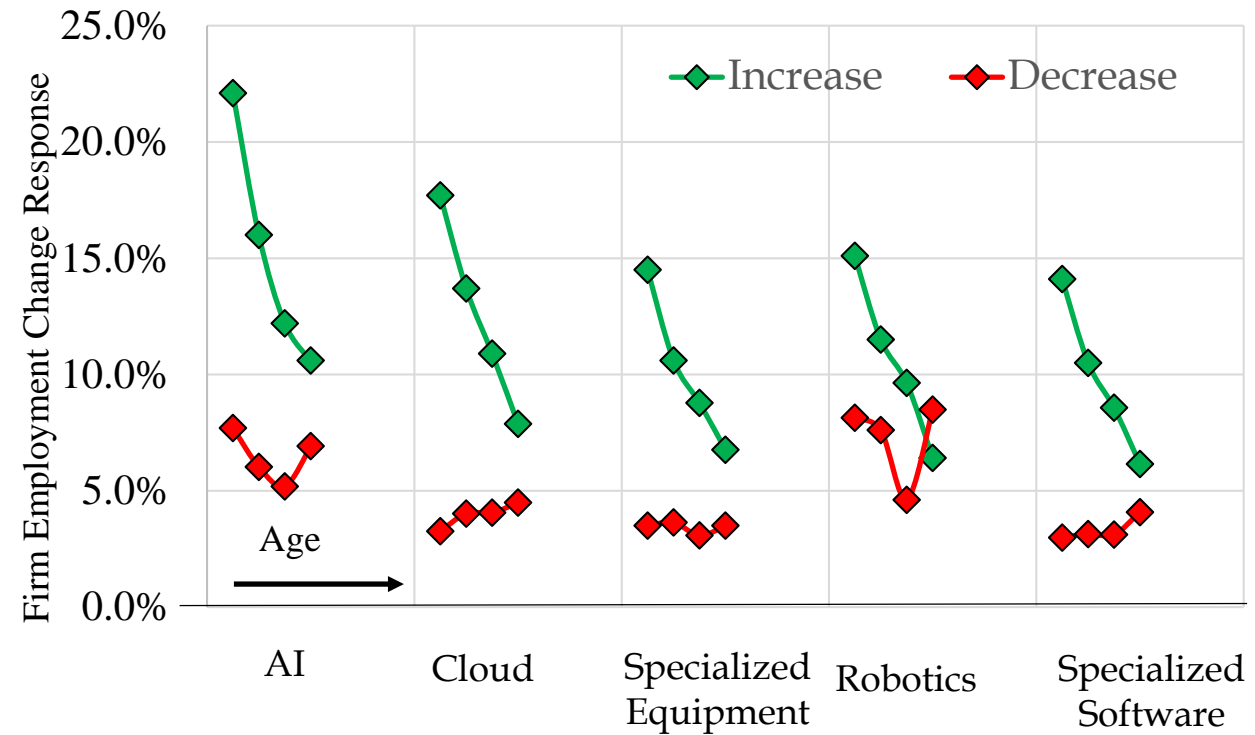
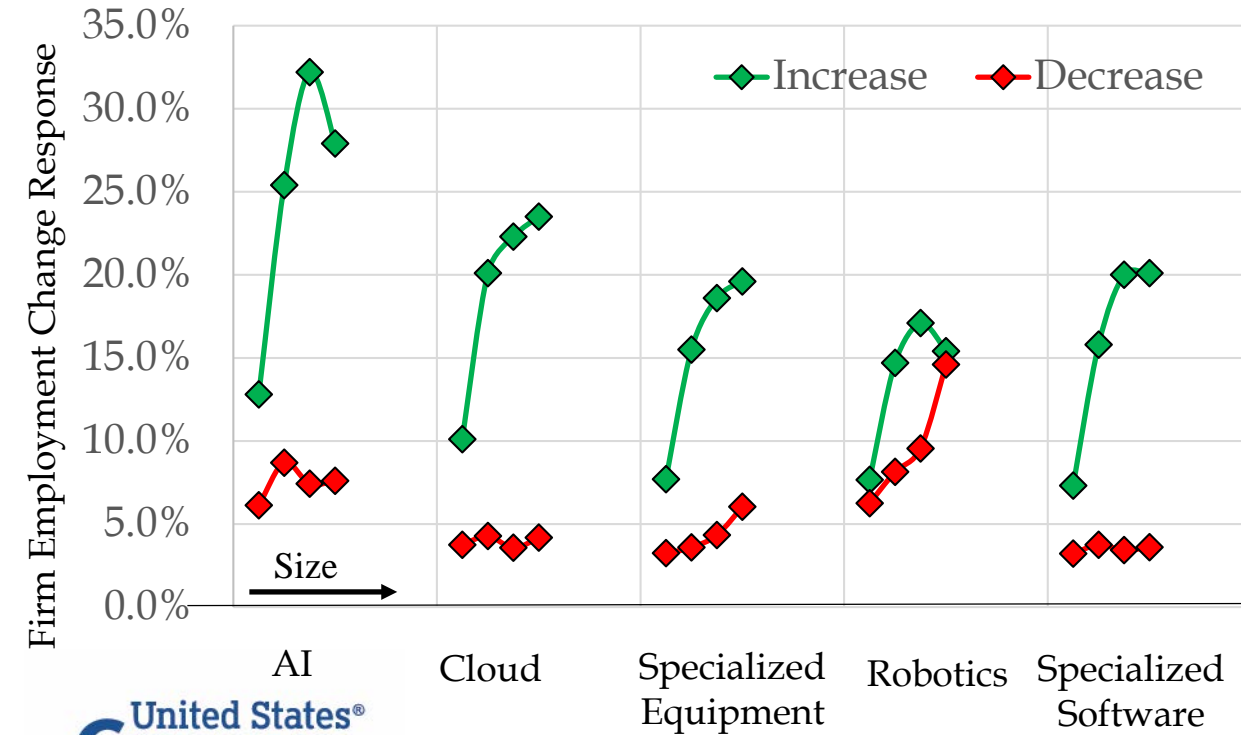


Employment Change by Size and Age

- Larger firms are *more likely* to report employment increases from technology adoption
- Older firms are *less likely* to report employment increases
- No clear pattern in reporting employment decreases, except for Robotics
- Intensity of use associated with higher share of employment increases

Net Change

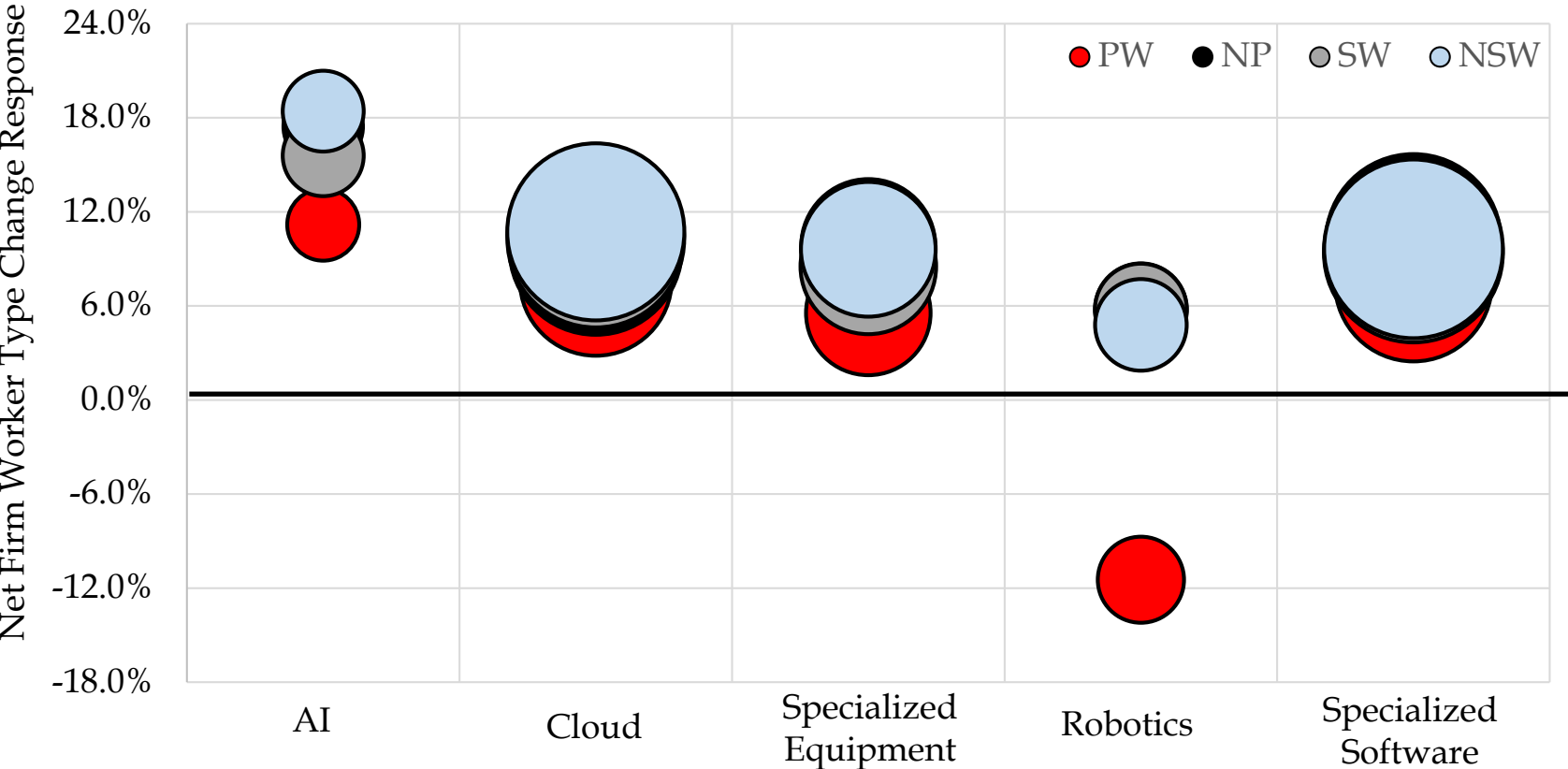
Intensity



Note: Firm-weighted. Size categories include: 1-9, 10-49, 50-249 and 250+ employees

Note: Firm-weighted. Age categories include: 0-5, 6-10, 11-20 and 21+

Net Response to Employment Change by Worker Type



- On average, more firms report employment increase for all worker types
- 12% more firms who adopt Robotics report decrease in employment of production workers
 - Driven by manufacturing firms

Firm-weighted

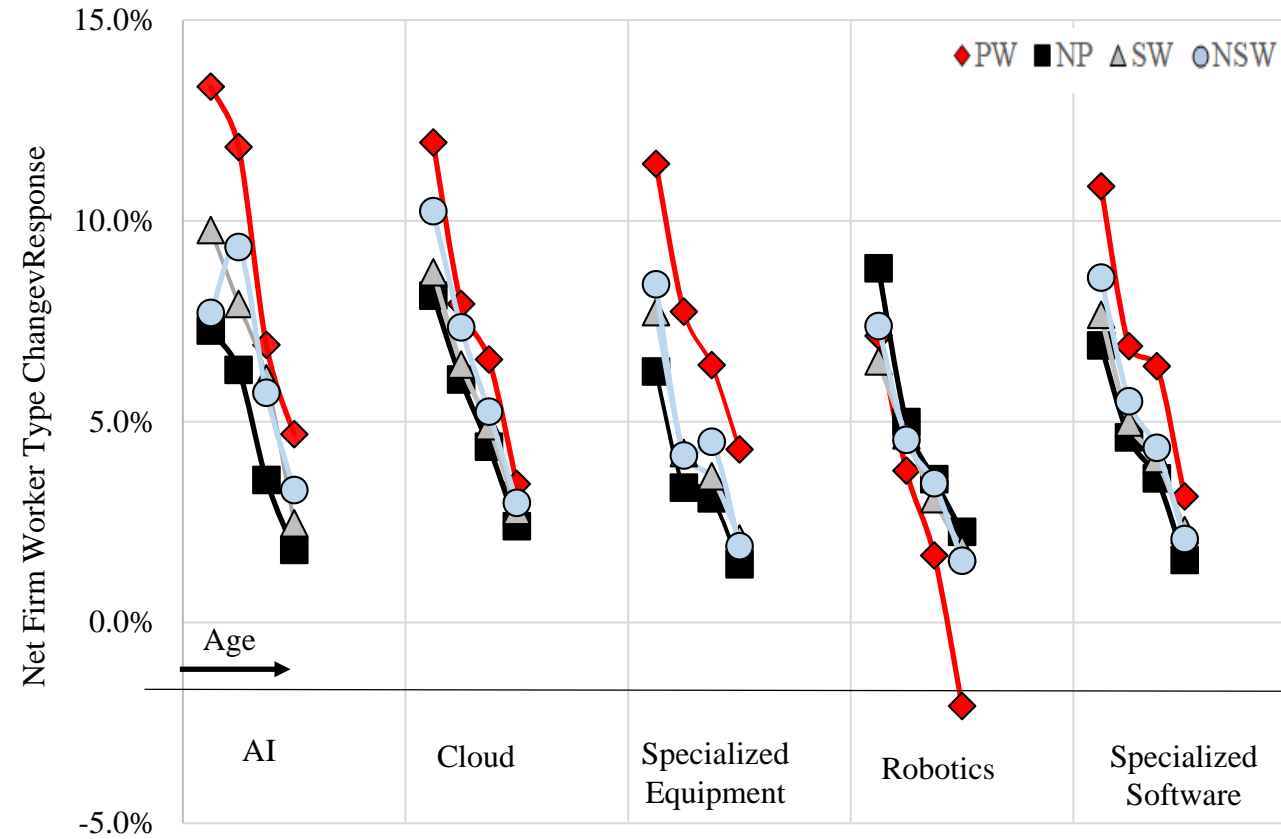
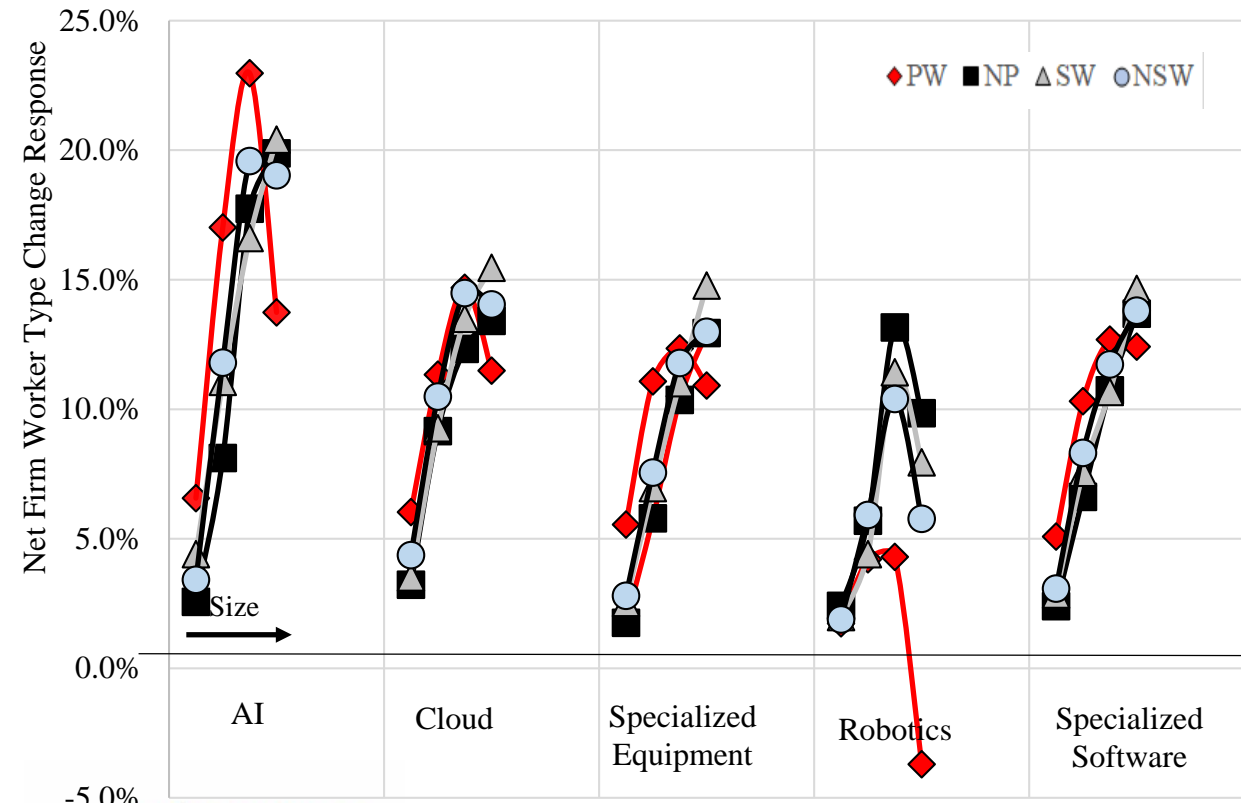
Production Workers & Manufacturing

Employment-weighted. Bubble size corresponds to number of adopters who employ worker type

Net Worker Type Changes by Size and Age

- Worker decomposition reveals similar patterns as Employment Change
- Production workers at largest and oldest firms more likely to decrease if firm adopts Robotics

Intensity



Note: Size categories include: 1-9, 10-49, 50-249 and 250+ employees

Note: Age categories include: 0-5, 6-10, 11-20 and 21+

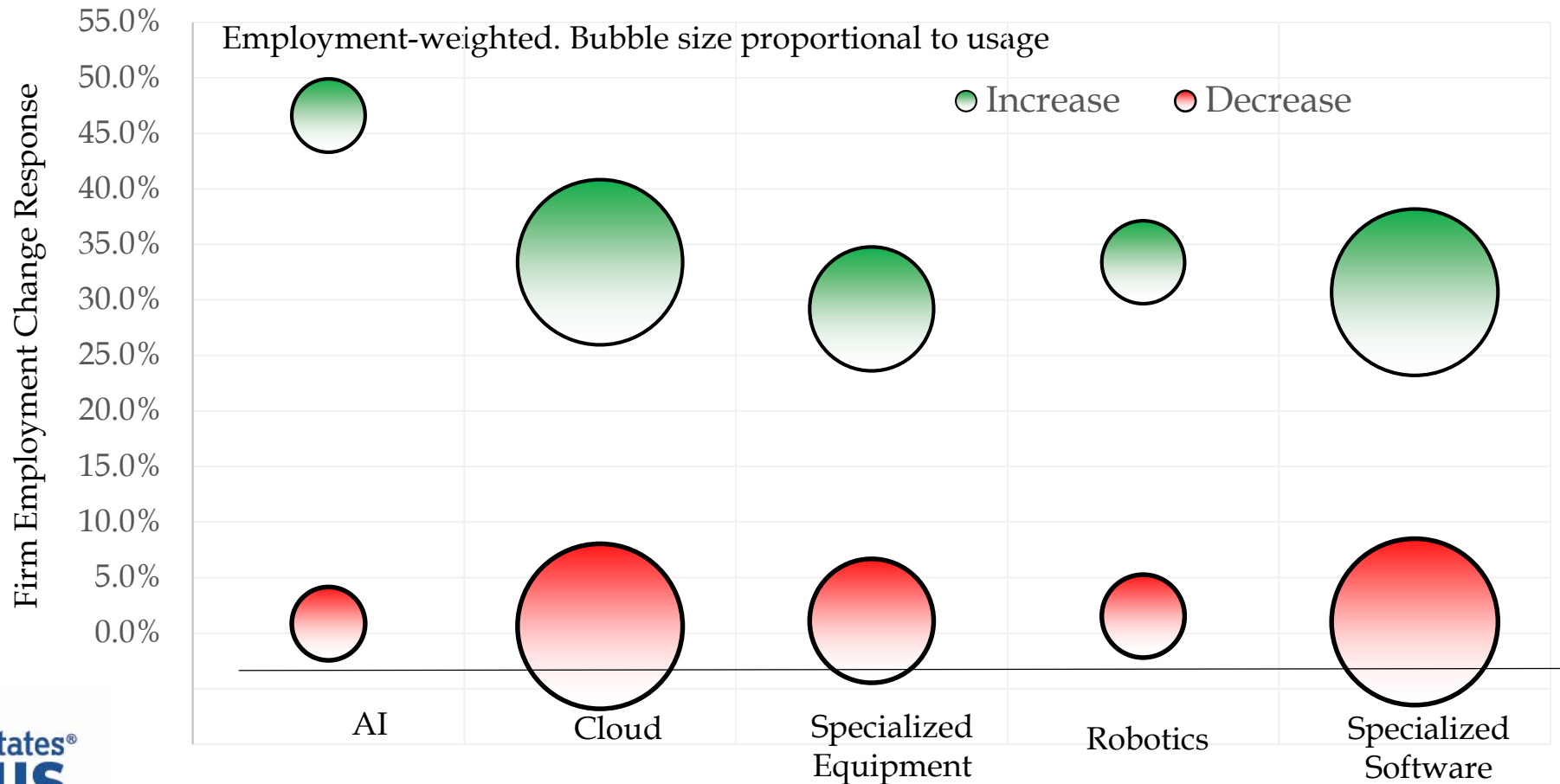
Skill Change by Technology Adoption

- About half of firms attribute changes in skill levels to technology adoption
- Very few firms attribute declining skill levels to technology adoption

Size and Age

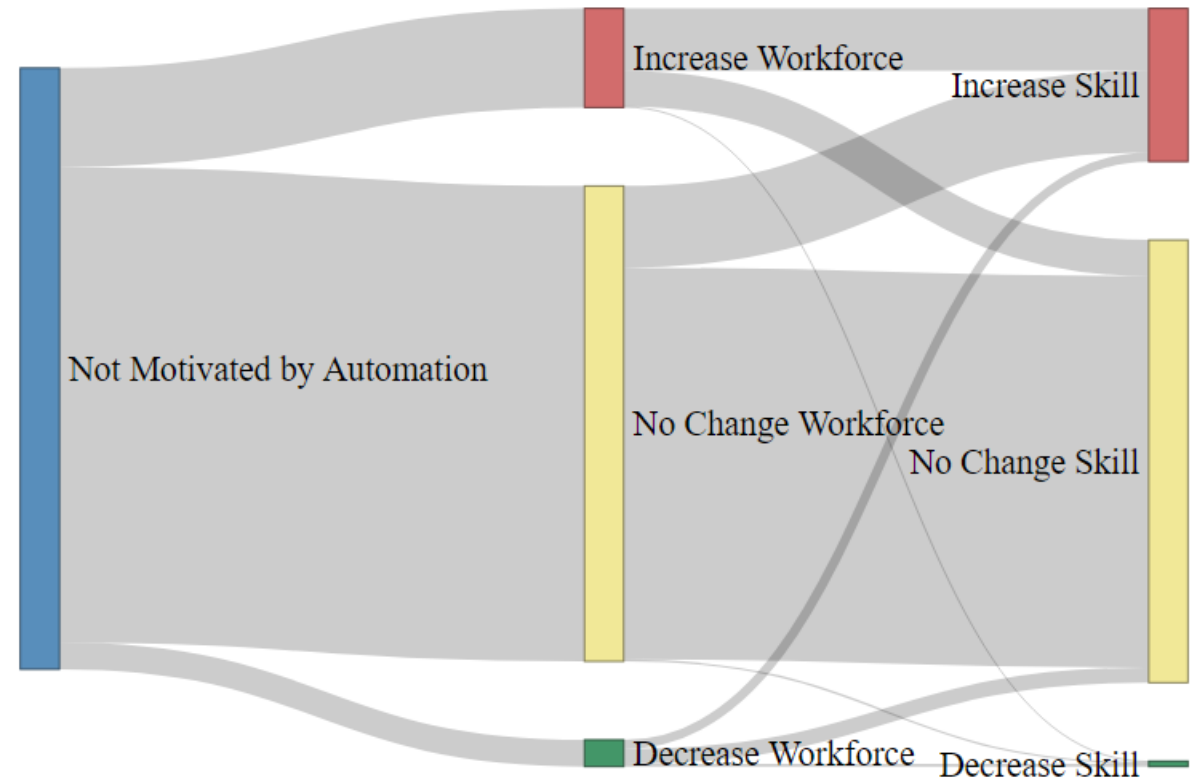
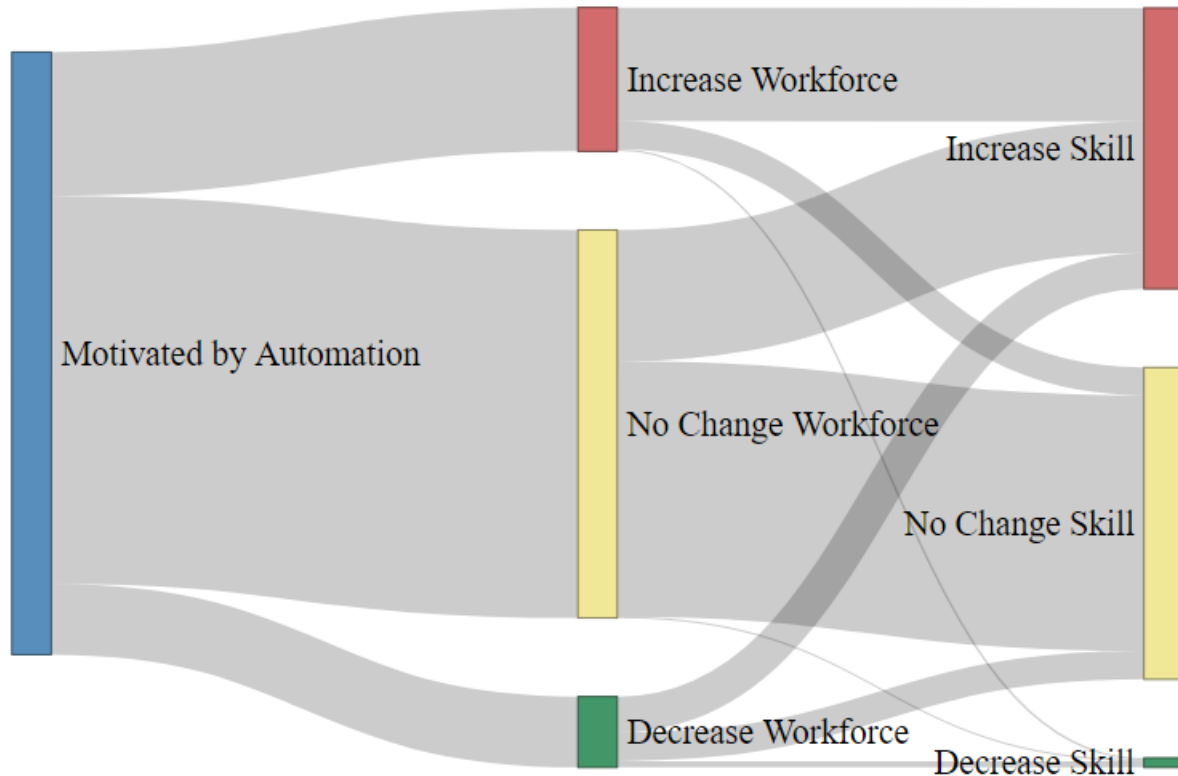
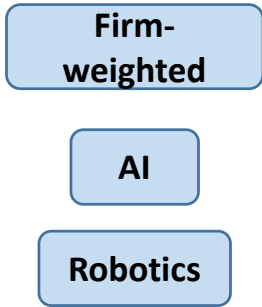
Intensity

Firm-weighted



Automation (Employment-weighted)

- Firms motivated by automation to adopt technologies are more likely to report increases in workforce and skill levels
- Majority of firms who automate and decrease workforce upgrade their skill



Challenges and Next Steps

- Further Validation
 - Using 2018 ABS and other Census data (ASM, LBD)
- Fix issues with non-response and “N/A” response options
 - Some inconsistencies
 - Many large, complex firms respond with “Don’t Know” or missing for all technologies
- Validation of self-responses using administrative longitudinal data
 - Attempt to identify adoption dates using existing Census surveys and Census data (e.g. import data for robotics, R&D and patent data for AI)
- Causality
 - Assess how combination of firm characteristics (size, age, industry, productivity, payroll per employee, number of establishments, etc...) impact adoption rates

Conclusion

- New measures of technology adoption, including AI and Robotics
 - Tech adoption for AI and Robotics is very low, worker exposure is higher
 - Skewed by sector towards largest and oldest firms
- Most firms motivated by upgrading processes and improving quality of processes
 - AI and Robotics more motivated by Automation
 - Large share of manufacturing workers exposed to automation through technology (specialized equipment and robotics)
- Technology adoption more likely to lead to no change in employment levels, but increased skills
 - Production workers more likely to be negatively impacted by Robotics
- Data will be made available soon!

Challenges
and Next
Steps

Thank you!

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Appendix

A.1 Overview of the 2019 Annual Business Survey

This section provides:

- An overview of the sampling for 2019 ABS
- How the LBD weights were developed
- Overview of 2018 ABS
 - Technology responses
- Comparison with 2018 Annual Business Survey

Annual Business Survey (ABS) Sampling

- The 2019 ABS sampling is stratified by ownership status, industry, and state from the 2018 Business Register
- Uses administrative data to estimate probability that firm is minority- or women-owned with each firm placed in one of 9 ownership frames for sampling (listed alphabetically)

American Indian	Asian	Black (or African American)	Hispanic	Native Hawaiian and Other Pacific Islands	Non-Hispanic White Men	Other (different race as write-in)	Publicly Owned	Women
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- Large companies are selected with certainty based on volume of sales, payroll, or number of paid employees
- Certain R&D industries are selected with certainty (e.g. NAICS 5417)
- R&D module (BRDIS-M) only asked of businesses with fewer than 10 employees

Constructing Tabulation Weights using LBD

- Motivation for Constructing New Weights
 - ABS sample frames based on business owner characteristics (e.g., race, ethnicity, sex)
 - Survey-weighted aggregation of employment, firm counts, etc. inconsistent with LBD
 - Latest extract does not include “corrections” for non-response
- Longitudinal Business Database (LBD)
 - Based on administrative records of employer firms – represents universe of employers
 - Includes firm age information (not available in ABS data)
 - More reliable employment data than ABS (some firms likely reporting payroll in the ABS)
- Methodology
 - Stratify based on size, age, and sector characteristics
 - 12 size and 12 age groups (as defined in BDS); and 19 sectors (two-digit NAICS)
 - Weight for firm in stratum s :

$$\frac{\text{Number of LBD firms in } s}{\text{Number of ABS firms in } s}$$



Comparing ABS and LBD weights

- Approximately 208,000 respondents linked with LBD (out of 300,000 possible)
- Self-constructed “LBD weights” match universe better than using survey weights, which were not updated to reflect the response rate
- Sectoral distributions also match more closely than using survey weights
- **Use LBD weights (firm-weighted) for all subsequent analysis, unless otherwise specified**

	2018 LBD (universe)	ABS (survey weights)	ABS (LBD weights)
Total Firms	6.1 million	3.8 million	6.1 million
Total Employment	141.7 million	82.5 million	143.0 million
Mean Employment	23.1	22.0	23.3
Mean Firm Age	14.2 years	14.9 years	14.2 years



Size and Age Distribution of ABS Sample

- LBD weights more closely reflect Business Dynamic Statistics
- More than $\frac{3}{4}$ of weighted firms have fewer than 10 employees
- 95 percent of weighted firms have fewer than 50 employees

Size Distribution

Employment	Unweighted	Weighted	BDS*
1 to 9	67	78	76
10 to 49	20	18	20
50 to 249	7	3	4
250 or more	6	1	1

Age Distribution

Age (Years)	Unweighted	Weighted	BDS*
0 to 5	28	34	33
6 to 10	15	16	17
11 to 20	24	22	23
21 or more	33	28	27

*BDS Statistics come from 2016 BDS as 2018 BDS statistics have different size/age categories



Sectoral Distribution of ABS Sample

All sectors represented. Survey skews more towards Manufacturing and Professional services, but is corrected

	Unweighted	Weighted	2018 LBD
NAICS 11,21-22 - Agriculture,..., Mining, Utilities	2	1	1
NAICS 23 - Construction	7	12	12
NAICS 31-33 - Manufacturing	18	4	4
NAICS 42 - Wholesale Trade	7	5	5
NAICS 44-45 - Retail Trade	7	11	10
NAICS 48-49 - Transportation & Warehousing	4	3	3
NAICS 51 - Information	5	1	1
NAICS 52-53 - Finance, Insurance, Real Estate	6	9	9
NAICS 54 - Professional Services	21	13	13
NAICS 55-56 - Management & Administrative	4	6	6
NAICS 61 - Education	1	2	2
NAICS 62 - Health Care	7	11	11
NAICS 71-72,81 - Other (Arts, Food, Other)	11	23	23

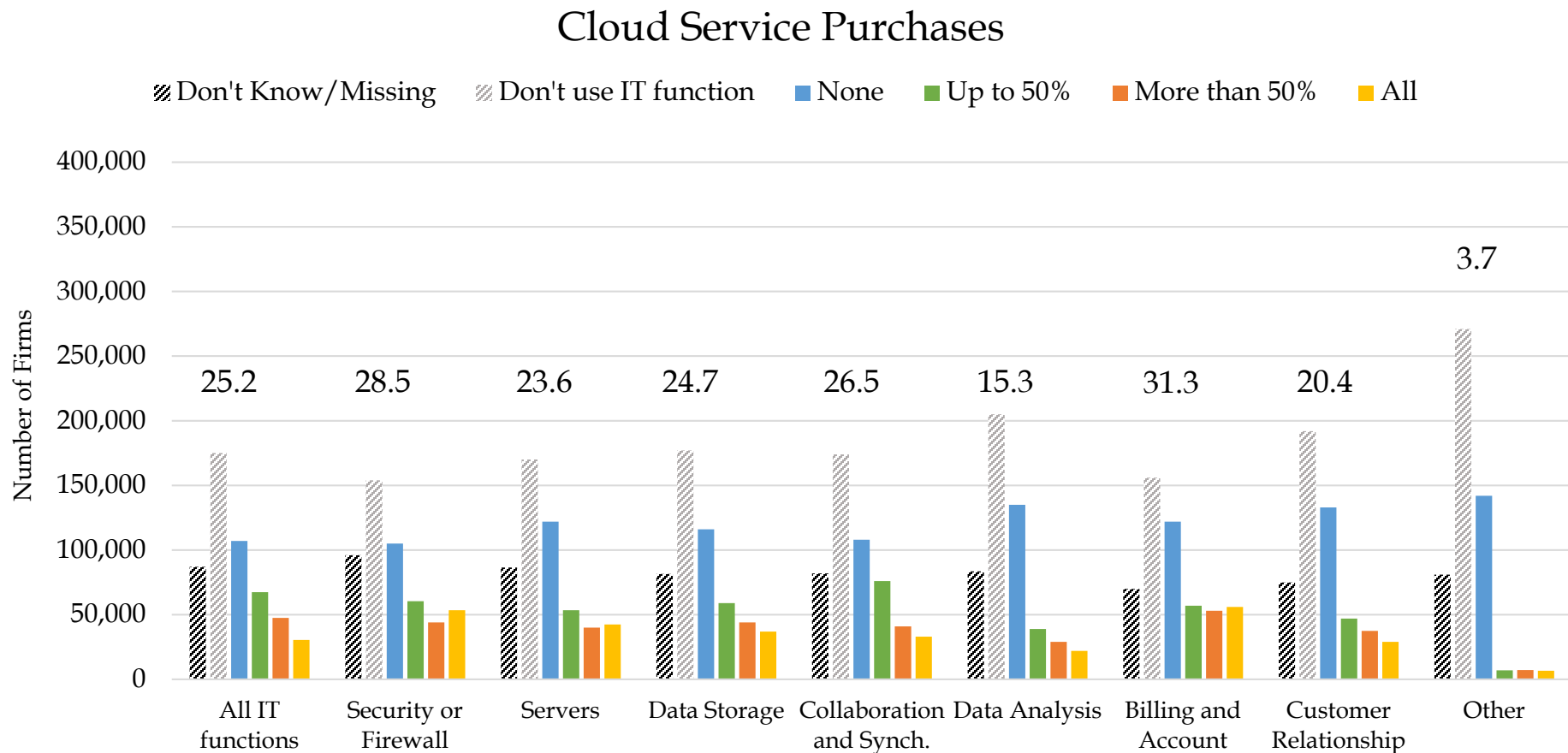


2018 Annual Business Survey (Overview)

- Significantly larger sample size (mailout was 850,000 potential respondents) than 2019 ABS (300,000)
- 2018 Annual Business Survey module included questions on adoption of “Digitization of Information”, “Cloud Purchases” and “Business Technologies”
- Some overlap with 2019 Annual Business Survey, including Cloud Purchases, AI and Robotics
- Similar aggregate adoption rates and size/age decomposition of adoption rates in overlapping technologies
- <https://www.census.gov/library/working-papers/2020/adrm/CES-WP-20-40.html>

2018 Annual Business Survey – Cloud Service Purchases (Question 2)

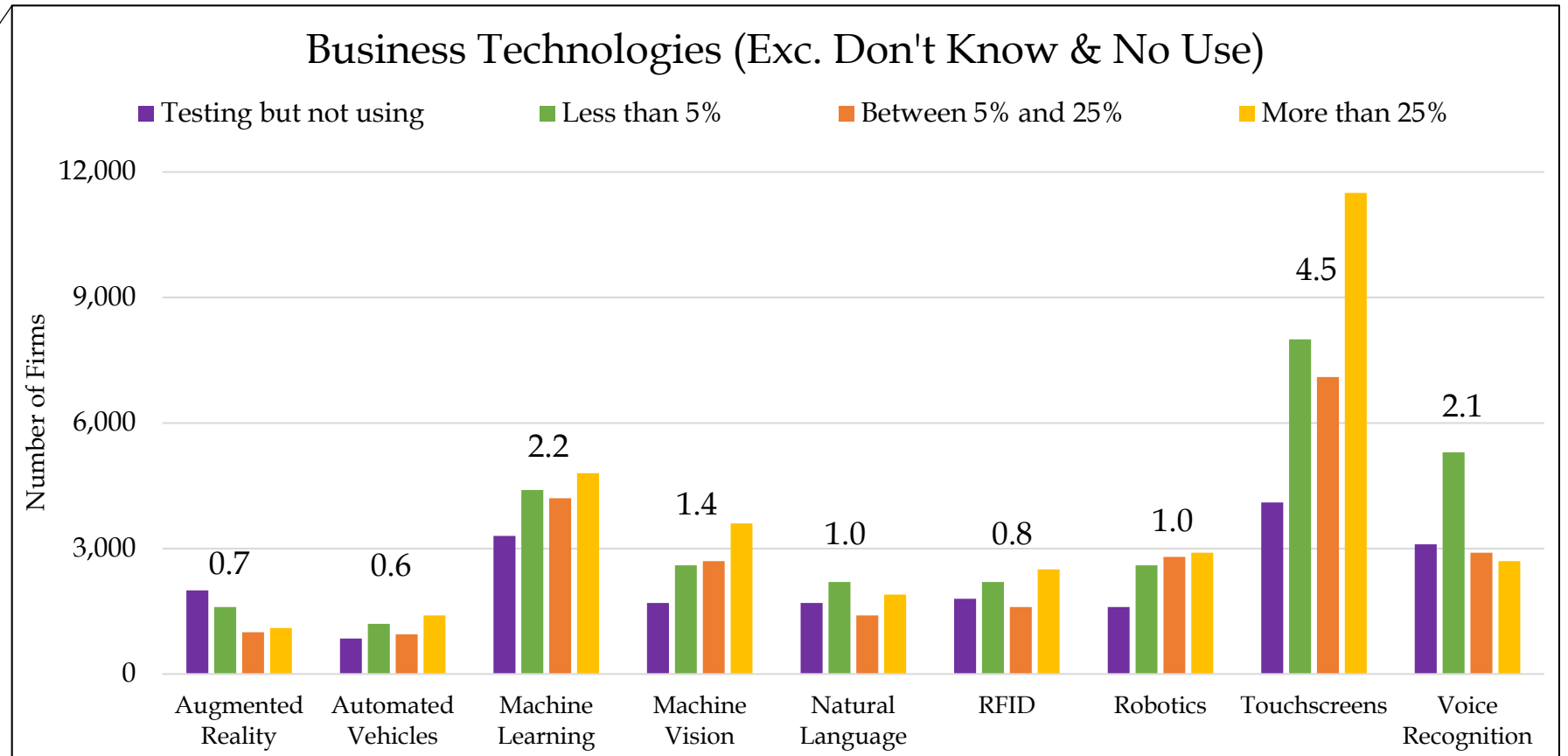
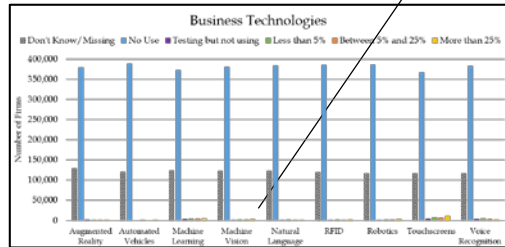
Considering the amount spent on each of these IT functions, how much was spent on cloud services?



*Number on top is total imputed usage rate

2018 Annual Business Survey – Business Technologies (Question 3)

In 2017, to what extent did this business use the following technologies in producing goods or services?



*Number on top is total imputed usage rate

Technology Comparison with 2018 ABS

Construct transition matrices between adoption of AI and Robotics from 2018 to 2019

AI	No Use in 2019	Testing in 2019	Use in 2019
No Use in 2018	0.97 (0.95)	0.00 (0.01)	0.03 (0.04)
Testing in 2018	0.78 (0.73)	0.09 (0.10)	0.13 (0.17)
Use in 2018	0.82 (0.78)	0.02 (0.04)	0.15 (0.19)

Robotics	No Use in 2019	Testing in 2019	Use in 2019
No Use in 2018	0.98 (0.95)	0 (0)	0.02 (0.04)
Testing in 2018	0.64 (0.57)	0.11 (0.14)	0.25 (0.29)
Use in 2018	0.46 (0.33)	0.02 (0.01)	0.53 (0.66)

*Employment-weighted in parentheses



- 2018 AI definition includes Machine Learning, Machine Vision, Natural Language Processing, Voice Recognition and Automated Guided Vehicles
- Large differences in AI response may be due to definitional differences or cognitive error
- Vast majority of “testers” decide to not adopt

A.2 - Firm Adoption of Technologies

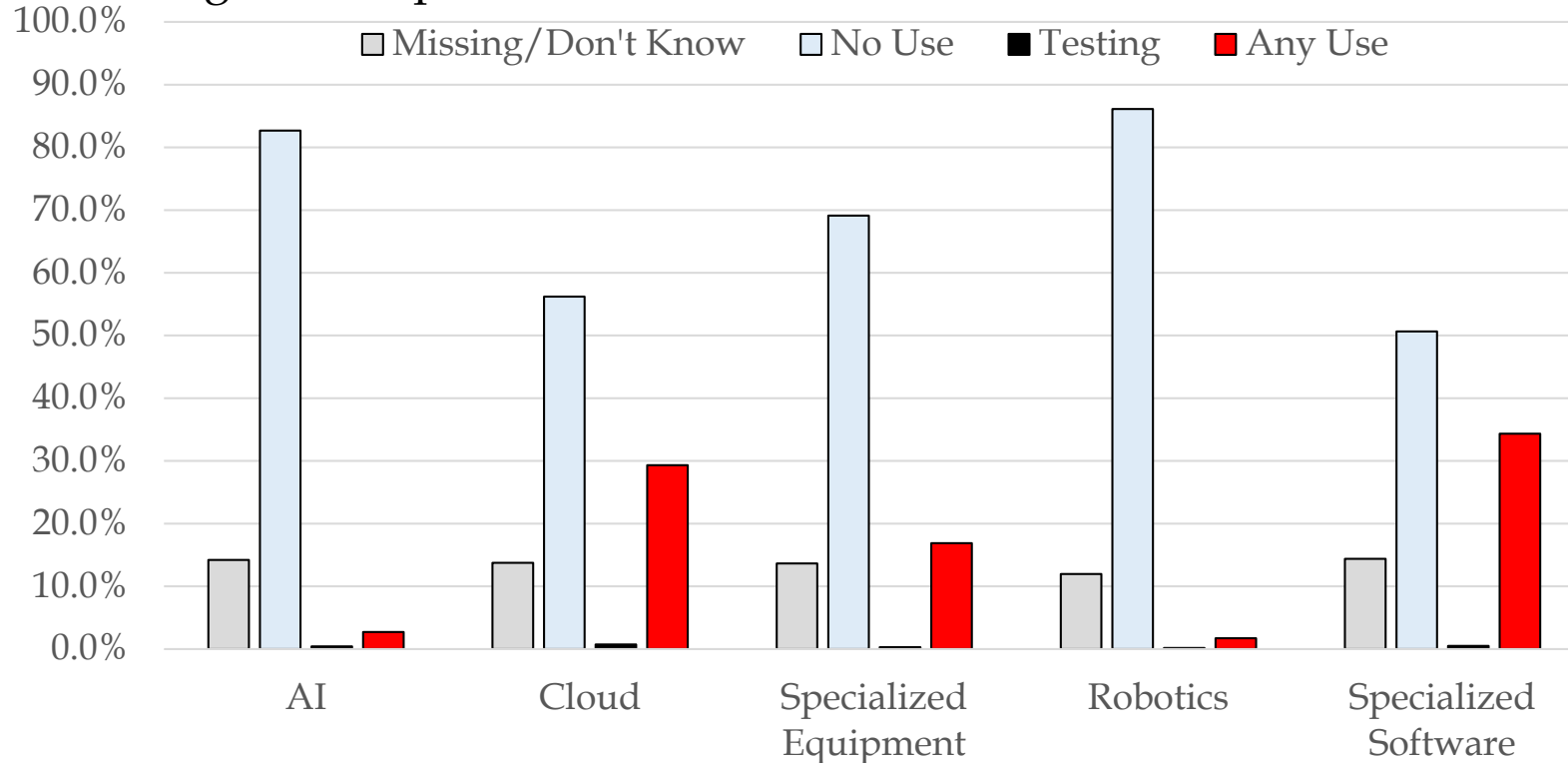
This section provides:

- Breakdown of firm response to each technology question
- Size/age heat maps of technology
- Industry employment-weighted breakdown of technology
- Top manufacturing industries (4-digit NAICS) that adopt AI or Robotics
- Number of technologies adopted by firm

Technology Use (Firm-weighted)

- “Not in use” is most common response for all technologies
- Specialized software and cloud computing are most common technologies,
- Robotics and AI are least common technologies
- Technology users make up a larger share of *employment* than they do of *firms*

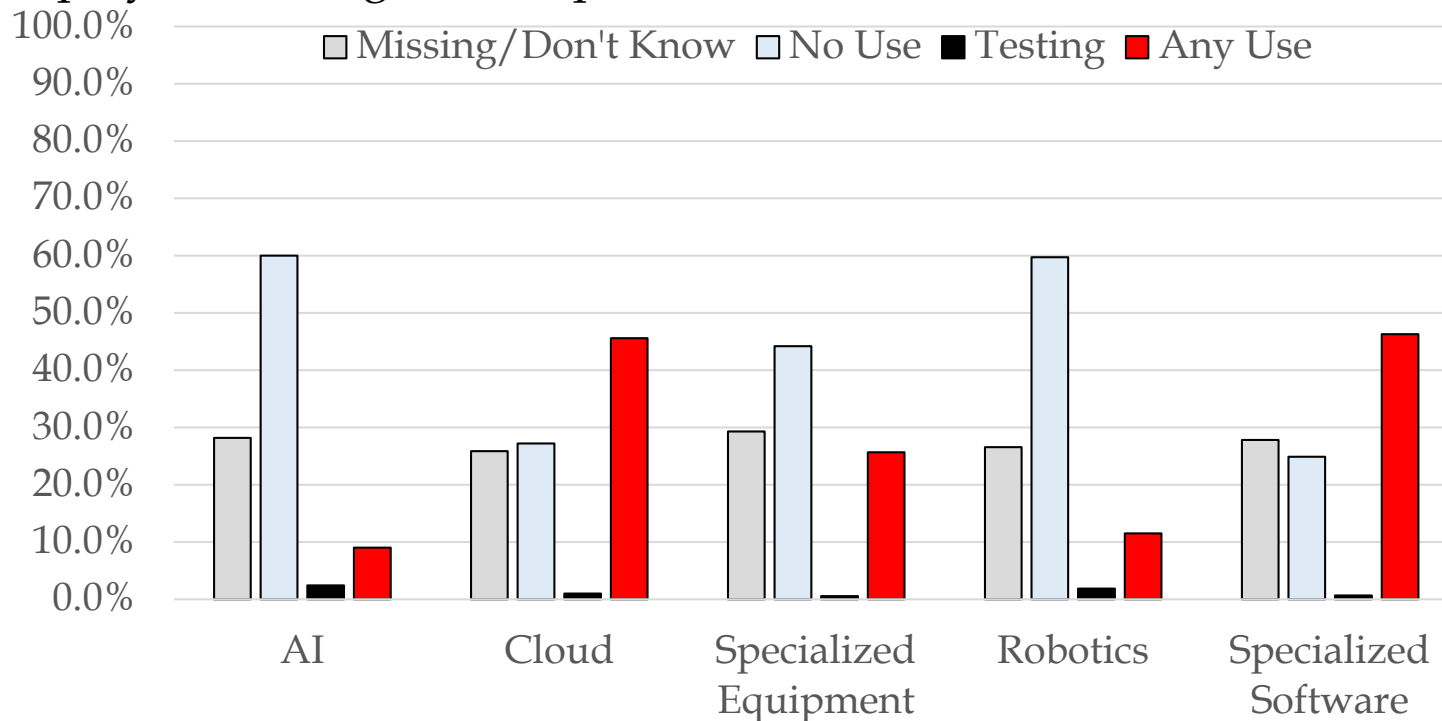
Firm-Weighted Responses



Technology Use (Employment-weighted)

- Employment-weighted responses reflect worker-level exposure to different technologies
- Usage rates are significantly higher for AI (+6pp), Cloud (+16pp), SE (+9pp), Robotics (+10pp) and SS (+12pp)
- Missing and Don't Know also significantly higher (2x higher on average)
 - Reflects item non-response by largest firms (see 2018 ABS Paper for discussion on imputation and dealing with item non-response)

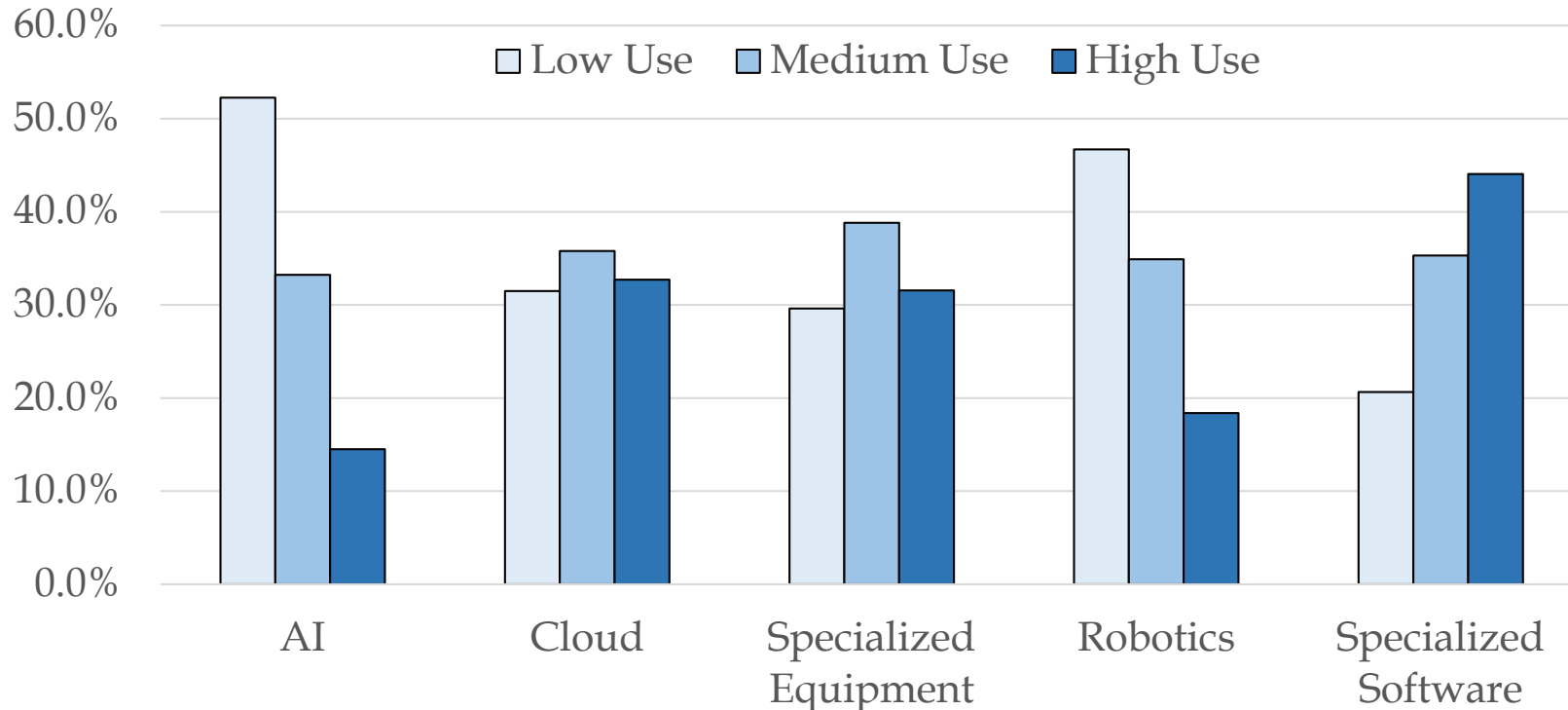
Employment-Weighted Responses



Technology Intensity (Firm-weighted, Cond. on Use)

- Most commonly adopted technology (i.e., specialized software) is also used the most intensively
- Employment-weighted intensive margins follow closely with firm-weighted
- Least commonly adopted technologies (i.e., robotics and AI) are also used the least intensively
 - Adverse factors preventing more adoption?

Firm-Weighted Responses



Technology Adoption by Size and Age

- Largest and oldest firms are most likely to adopt a technology
- Size and technology adoption association is monotonic... Age is more nuanced (younger firms adopt more when small, but older firms adopt more when large)

AI				
Age/Size	0-9 Emp	10-49 Emp	50-249 Emp	250+ Emp
0-5 Years	0.04 (0.04)	0.04 (0.05)	0.06 (0.06)	0.06 (0.06)
6-10 Years	0.03 (0.03)	0.04 (0.04)	0.05 (0.06)	0.07 (0.09)
11-20 Years	0.03 (0.03)	0.04 (0.04)	0.06 (0.06)	0.10 (0.13)
21+ Years	0.02 (0.02)	0.03 (0.03)	0.04 (0.04)	0.07 (0.21)

Cloud				
Age/Size	0-9 Emp	10-49 Emp	50-249 Emp	250+ Emp
0-5 Years	0.36 (0.39)	0.46 (0.47)	0.58 (0.59)	0.68 (0.69)
6-10 Years	0.32 (0.35)	0.46 (0.48)	0.62 (0.63)	0.66 (0.67)
11-20 Years	0.29 (0.32)	0.43 (0.44)	0.57 (0.58)	0.69 (0.71)
21+ Years	0.23 (0.27)	0.38 (0.41)	0.53 (0.55)	0.69 (0.75)

Specialized Equipment				
Age/Size	0-9 Emp	10-49 Emp	50-249 Emp	250+ Emp
0-5 Years	0.18 (0.21)	0.25 (0.25)	0.27 (0.28)	0.30 (0.23)
6-10 Years	0.17 (0.2)	0.25 (0.25)	0.29 (0.29)	0.20 (0.24)
11-20 Years	0.17 (0.2)	0.27 (0.27)	0.30 (0.31)	0.31 (0.29)
21+ Years	0.18 (0.22)	0.27 (0.28)	0.34 (0.36)	0.34 (0.47)

Robotics				
Age/Size	0-9 Emp	10-49 Emp	50-249 Emp	250+ Emp
0-5 Years	0.02 (0.02)	0.03 (0.03)	0.04 (0.04)	0.06 (0.05)
6-10 Years	0.02 (0.02)	0.03 (0.03)	0.05 (0.05)	0.06 (0.08)
11-20 Years	0.01 (0.02)	0.03 (0.03)	0.05 (0.06)	0.10 (0.12)
21+ Years	0.01 (0.01)	0.03 (0.03)	0.06 (0.07)	0.13 (0.28)

Specialized Software				
Age/Size	0-9 Emp	10-49 Emp	50-249 Emp	250+ Emp
0-5 Years	0.38 (0.42)	0.5 (0.51)	0.57 (0.58)	0.71 (0.69)
6-10 Years	0.37 (0.41)	0.52 (0.53)	0.60 (0.61)	0.65 (0.69)
11-20 Years	0.36 (0.40)	0.51 (0.52)	0.63 (0.64)	0.70 (0.70)
21+ Years	0.34 (0.40)	0.5 (0.52)	0.61 (0.63)	0.71 (0.75)



Note: All table values are the estimated coefficients on size-age interactions in a linear probability model (LPM) regression with technology use as the dependent variable. No other controls were included in the regression. Employment-weighted numbers are included in parentheses.

Technology Adoption by Sector (Firm-weighted)

- Some big sectoral differences in employment-weighted technology adoption rates – “Transportation and warehousing” and “Agriculture” are major users of AI and Robotics

	AI (%)	Cloud (%)	Specialized Equipment (%)	Robotics (%)	Specialized Software (%)
Agriculture,..., Mining, Utilities	1.1	18.5	23.1	1.3	26.1
Construction	1.9	24.2	18.2	1.2	26.5
Manufacturing	3.1	31.0	39.9	8.7	42.1
Wholesale Trade	2.2	31.5	16.0	2.3	33.7
Retail Trade	2.6	25.6	15.6	2.0	32.7
Transportation & Warehousing	2.6	24.7	14.5	0.8	30.1
Information	8.2	60.4	22.6	2.5	62.6
Finance, Insurance, Real Estate	4.0	46.0	6.9	0.7	49.6
Professional Services	6.3	54.6	19.2	3.4	60.3
Management & Administrative	2.6	31.1	16.4	0.9	33.8
Education	2.4	47.8	12.9	1.0	46.8
Health Care	3.5	42.9	32.4	2.5	53.3
Other (Arts, Food, Other)	2.0	23.0	19.9	1.0	31.7



Top Manufacturing Industries for Automation Technologies (AI & Robotics)

Top NAICS for AI Adoption	Firm-Weighted	Employment-Weighted
3341 - Computer and Peripheral Manufacturing	6.1%	20.0%
3251 - Basic Chemicals	6.0%	5.9%
3345 - Navigation and Control Instrument	5.6%	31.3%
3334 - HVAC Manufacturing	4.4%	31.3%
3115 - Dairy Product Manufacturing	4.2%	32.1%

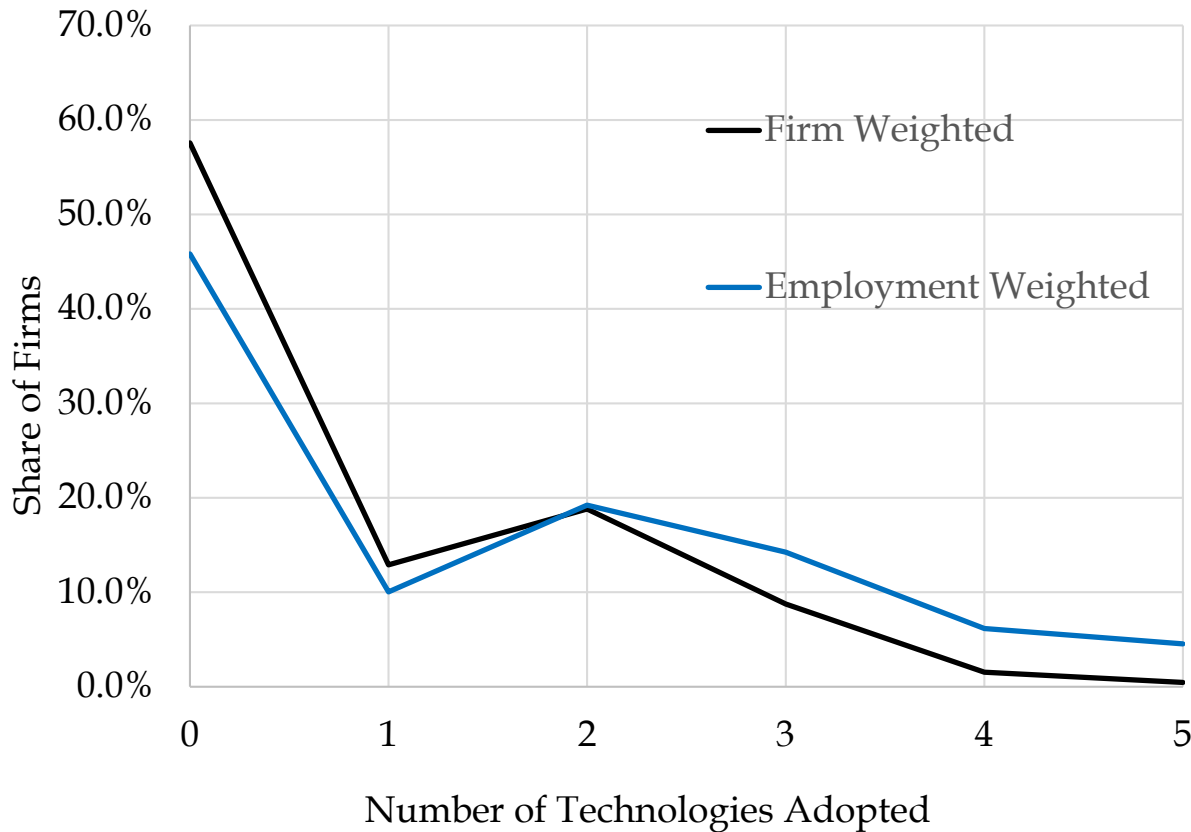
- AI is most commonly found in Computer and Electronic Manufacturing (NAICS 334)

Top NAICS for Robotics Adoption	Firm-Weighted	Employment-Weighted
3221 - Forging	20.6%	81.8%
3363 - Motor Vehicle	19.7%	67.2%
3325 - Hardware	19.4%	87.4%
3311 - Iron & Steel Mills	16.4%	34.9%
3115 - Dairy Product Manufacturing	14.0%	75.4%

- Robotics most commonly found in heavy machinery manufacturing



Number of Technologies Adopted



- 58 of Firms do not adopt *any* technology
- Largest firms adopt multiple technologies
- Firms who adopt a technology are more likely to adopt 2 technologies
- Most common technology pairings include:
 1. Cloud and Specialized Software
 2. Cloud, Specialized Software and Equipment
 3. Specialized Software and Equipment



A.3 - Motivation and Adverse Factors for Adoption

This section provides:

- Summary of Motivation Responses (Firm-weighted)
- Summary of Motivation Responses by Size and Age
- Summary of Motivation Responses by Manufacturing Status
- Firm exposure to Automation
- Employment-weighted adverse factors
- NA and No adverse factors (Firm-weighted)
- NA and No adverse factors (Employment-weighted)

Motivation for Technology Adoption (Firm-weighted)

For employees of firms that use AI or Robotics, more than half are employed by firms that adopted AI or Robotics for the purpose of Automation*

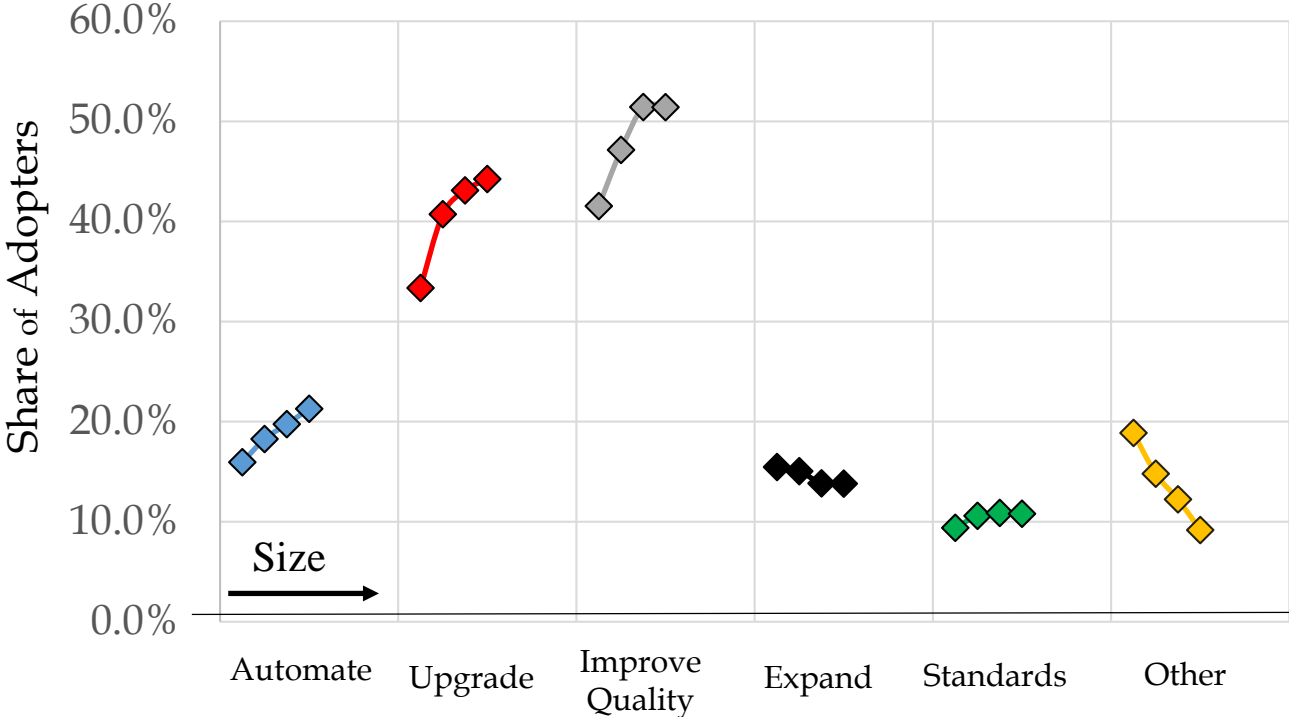
Technology	Improve						# of Firms (000s)	# of Workers
	Automate	Upgrade	Quality	Expand	Standards	Other		
AI	29.0%	36.6%	49.8%	24.8%	11.8%	18.7%	166	12.9M
Cloud	16.0%	42.9%	49.8%	14.5%	10.7%	16.0%	1,794	65.2M
Specialized Equipment	20.4%	37.9%	51.3%	25.5%	11.0%	17.7%	1,033	36.7M
Robotics	39.6%	31.1%	45.8%	24.1%	8.2%	20.8%	106	16.4M
Specialized Software	20.3%	43.2%	51.4%	15.8%	12.2%	19.2%	2,102	66.2M

*Note: Here “automation” specifically means the automation of tasks performed by labor.

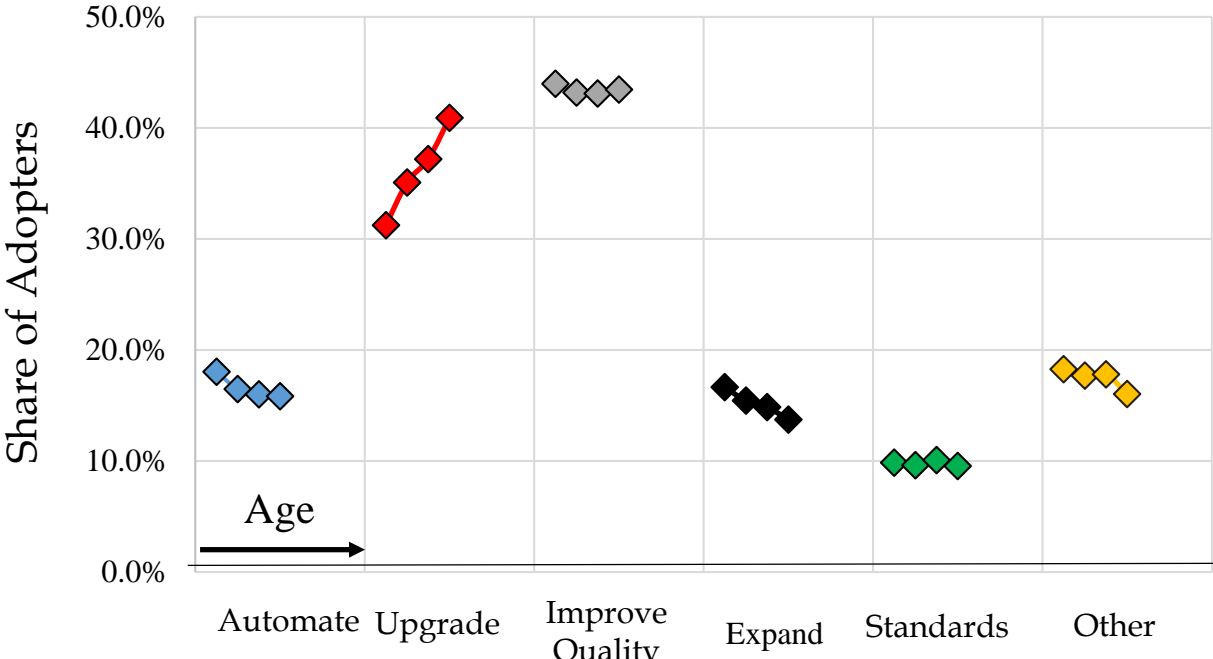


Motivation by Size and Age

- Motivation for Automation, Process Upgrade and Quality Improvements increases as firms get bigger
- Motivation for Process Upgrading increases as firms get older



Note: Size categories include: 0-9, 10-49, 50-249 and 250+ employees

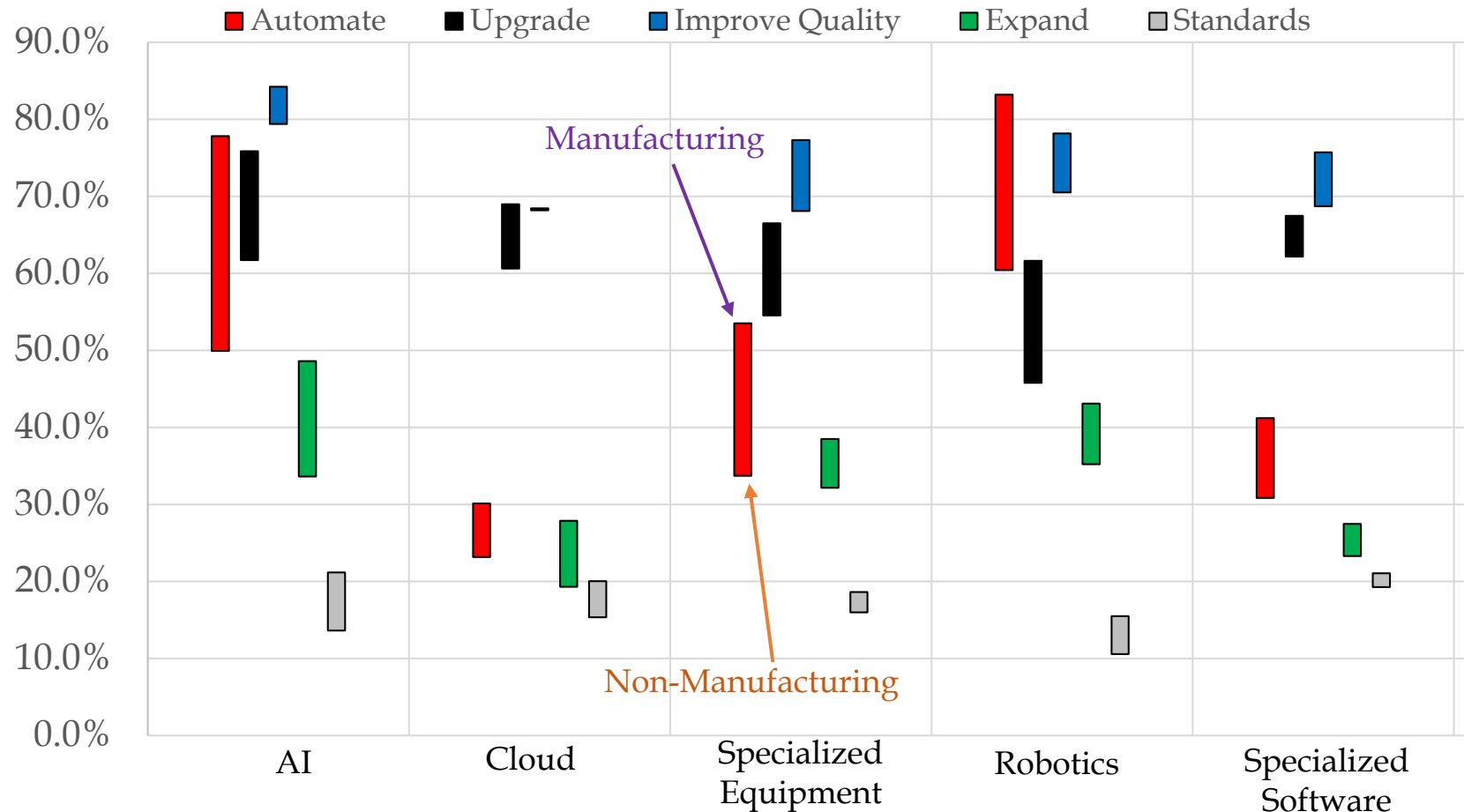


Note: Age categories include: 0-5, 6-10, 11-20 and 21+



Net Difference in Motivation by Manufacturing Status

Manufacturing firms adopting AI, Robotics, and Specialized Equipment much more likely to be motivated by Automation



*Bars reflect difference in Motivation responses by Technology type between Manufacturing and non-Manufacturing Firms
 **Robotics-Expand and Cloud-Improve Quality have more non-manufacturing firms than manufacturing

Firm Exposure to Automation

- Small share of firms motivated to adopt a technology by automation
- Size and sector are key determinants of automation usage by firm

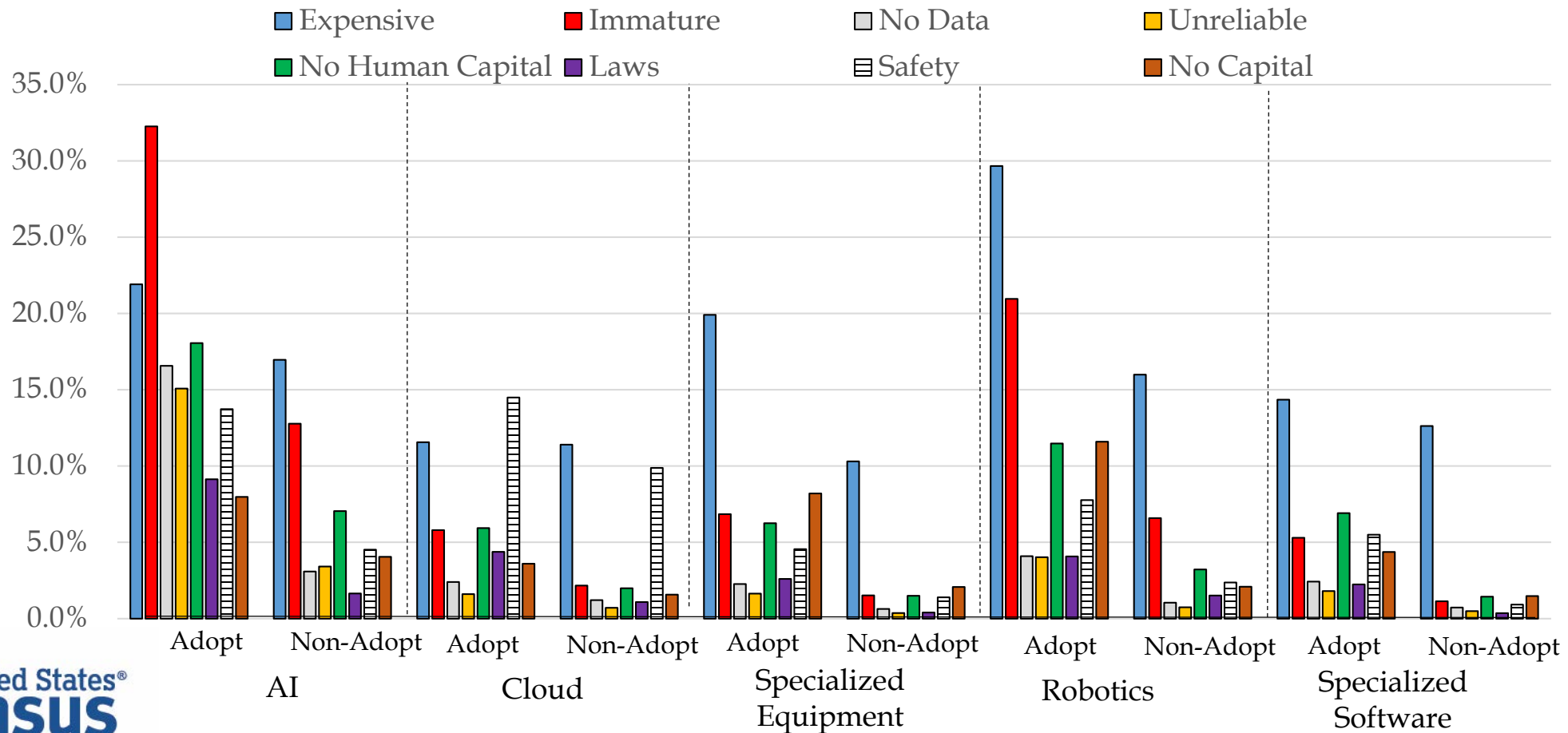
Firm Exposure to Automation by Technology (%)`

Type	AI	Cloud Comp.	Spec. Soft.	Robotics	Spec. Equip.
All	0.9	5.4	4.0	0.8	8.1
Manufacturing	1.2	4.4	13.4	5.3	10.2



Adverse Factors for Technology Adoption (Employment-weighted)

- Employment-weighted adverse factors highlight immaturity and cost of technology for adopters
- Lack of human capital is major factor preventing adoption of AI and Robotics
- AI has several factors, including Unreliability, lack of data and security

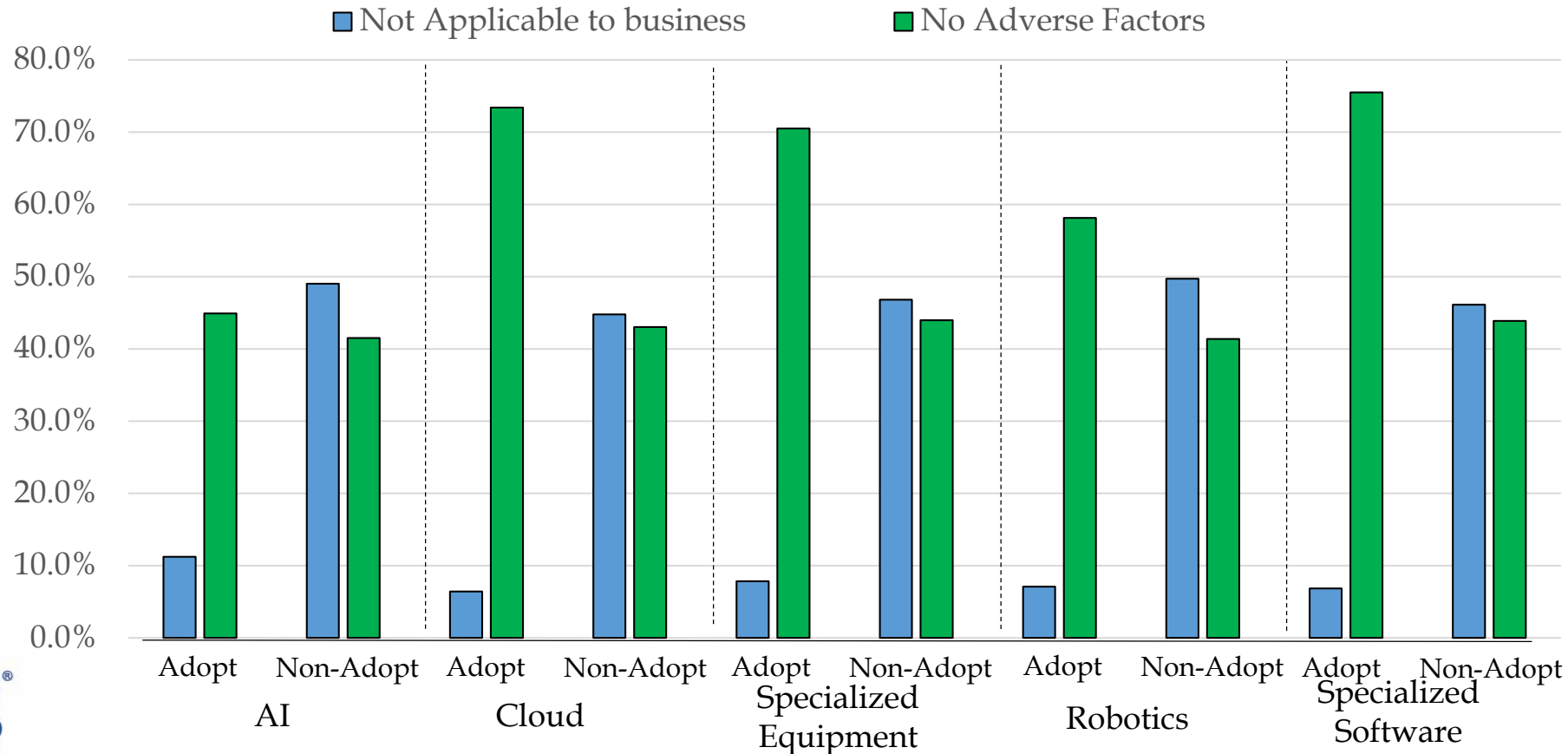


*Conditional on technology being applicable. "No adverse factors" category is dropped in figure.



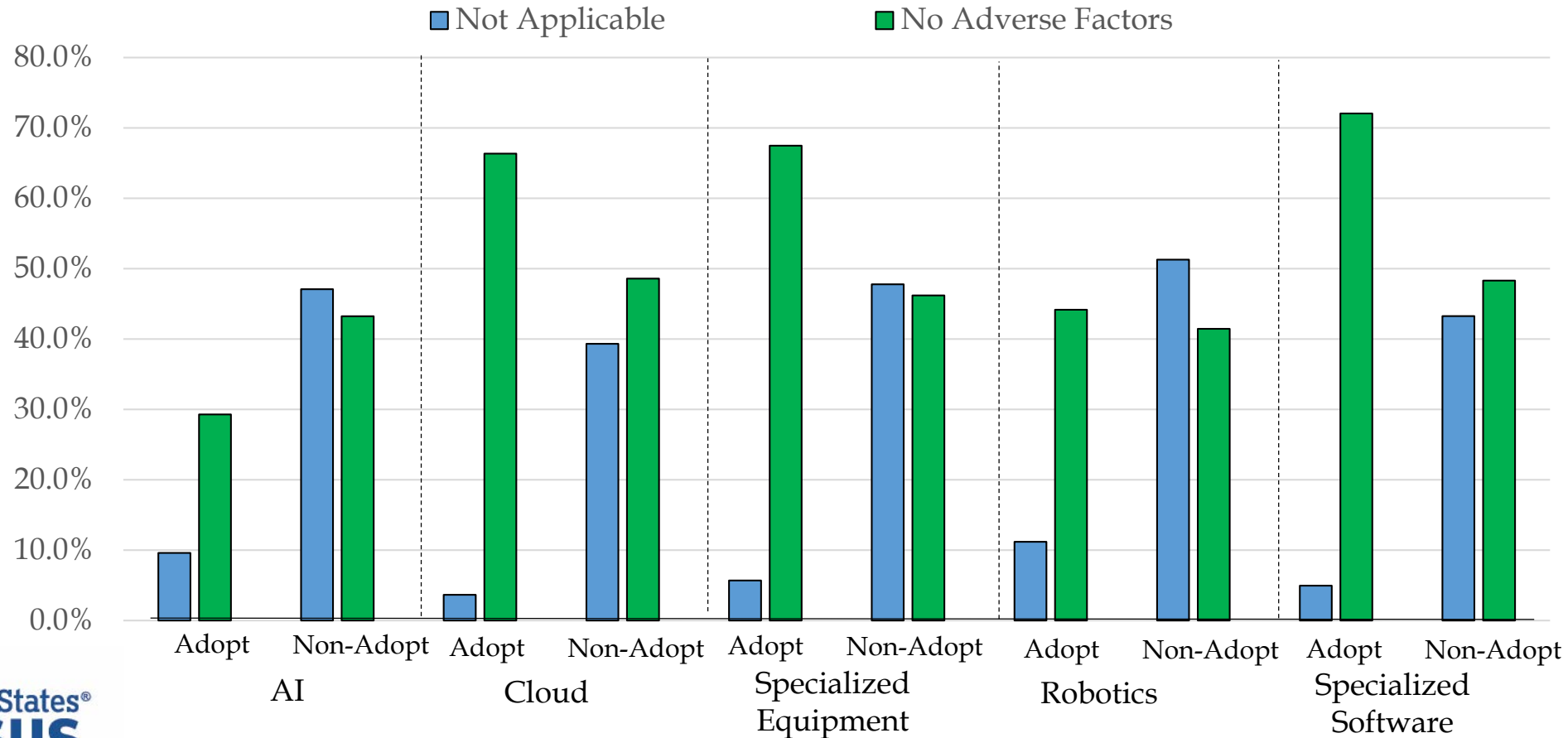
NA and Adverse Factors for Technology Adoption (Firm-weighted)

- Majority of non-adopters report “Not Applicable” or “No Adverse Factors” preventing adoption (80-90% of respondents)



NA and Adverse Factors for Technology Adoption (Employment-weighted)

- Majority of non-adopters report “Not Applicable” or “No Adverse Factors” preventing adoption (80-90% of respondents)



A.4 - Employment Outcomes from Adoption

This section provides:

- Generalized Ordered Logit framework
- Employment changes from tech (firm-weighted)
- Net Difference in Firm Responses to changes in worker type (firm-weighted)
- Production Worker Changes by Manufacturing status (employment-weighted)
- Skill changes from tech (firm-weighted)
- Net Difference in Firm Responses to Employment Changes by Size, Age and intensity (firm-weighted)
- Net difference in Firm Responses to changes in worker types by intensity (firm-weighted)
- Net Difference in Firm Responses to Skill Changes by Size, Age and intensity (firm-weighted)
- Sankey diagram on employment and skill change by automation (firm-weighted)
- Sankey diagram on employment and skill change by AI and Robotics (firm-weighted)
- Sankey diagram on production worker change from Robotics (employment-weighted)
- Challenges and Next Steps

Generalized Ordered Logit Specification (Tech Use)

- Estimate the following two equations for each technology $tech$:

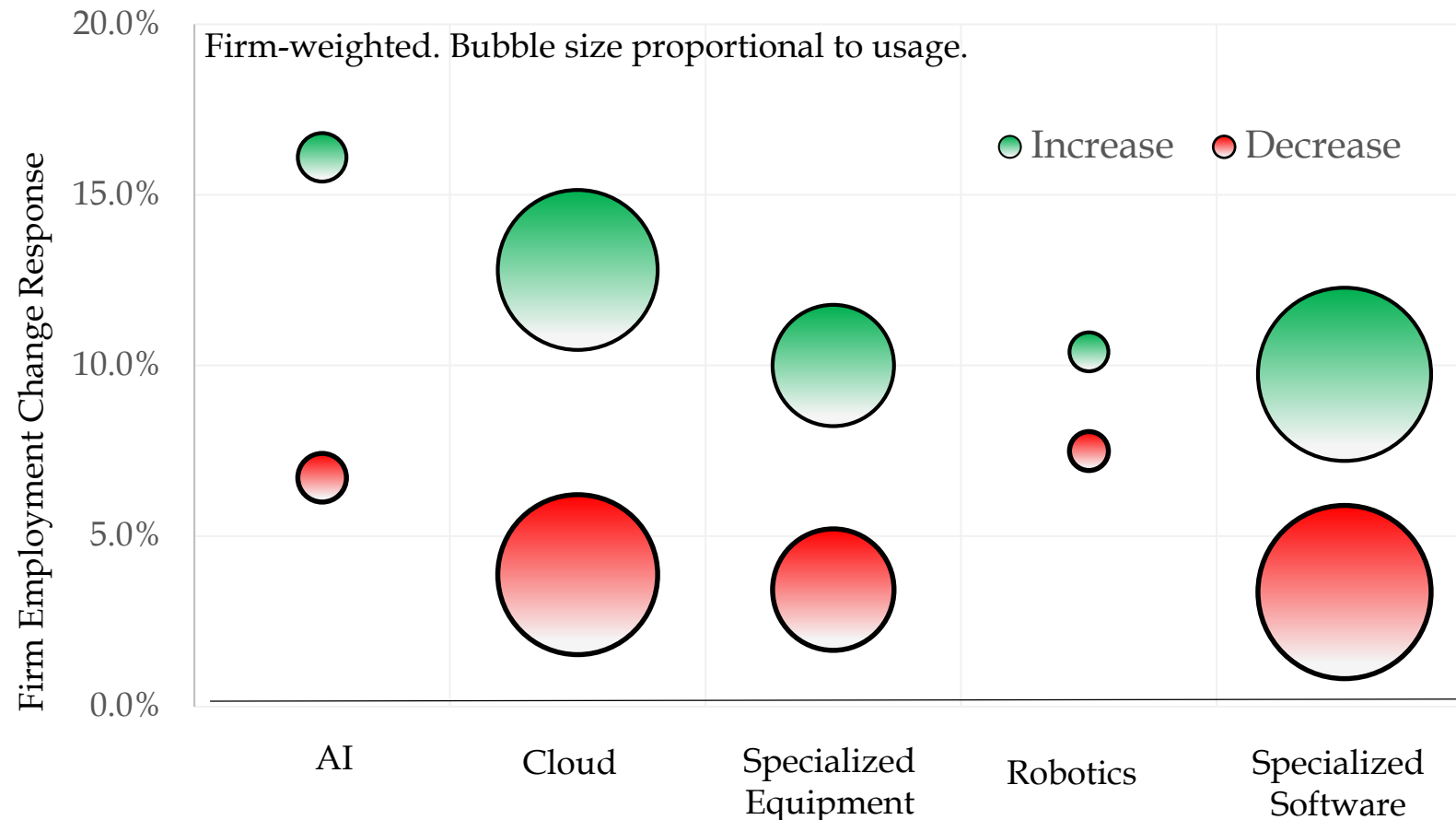
$$\ln \left(\frac{p_j^{dec}}{p_j^{nc} + p_j^{inc}} \right)^{tech} = \alpha_{tech}^{dec} + X_j' \gamma_{tech}^{dec} \quad (1)$$

$$\ln \left(\frac{p_j^{dec} + p_j^{nc}}{p_j^{inc}} \right)^{tech} = \alpha_{tech}^{nc} + X_j' \gamma_{tech}^{nc} \quad (2)$$

- Firm level (conditional on adoption of $tech$): firm j
- X_j : vector of firm characteristics including two-digit NAICS sectors, 4 size bins, and 4 age bins
- $\gamma_{tech}^{dec}, \gamma_{tech}^{nc}$: effect of firm characteristics on log odds ratio of the event ($\Delta emp_{tech} \leq -1$) or ($\Delta emp_{tech} \leq 0$), respectively
 - For worker types (PW, NP, SW and NSW), we drop observations who do not employ specific worker type
- *Proportional odds/parallel lines* assumption: $\gamma_{tech}^{dec} = \gamma_{tech}^{nc}$
 - Wald test \Rightarrow reject proportional odds model in favor of **partial proportional odds** model

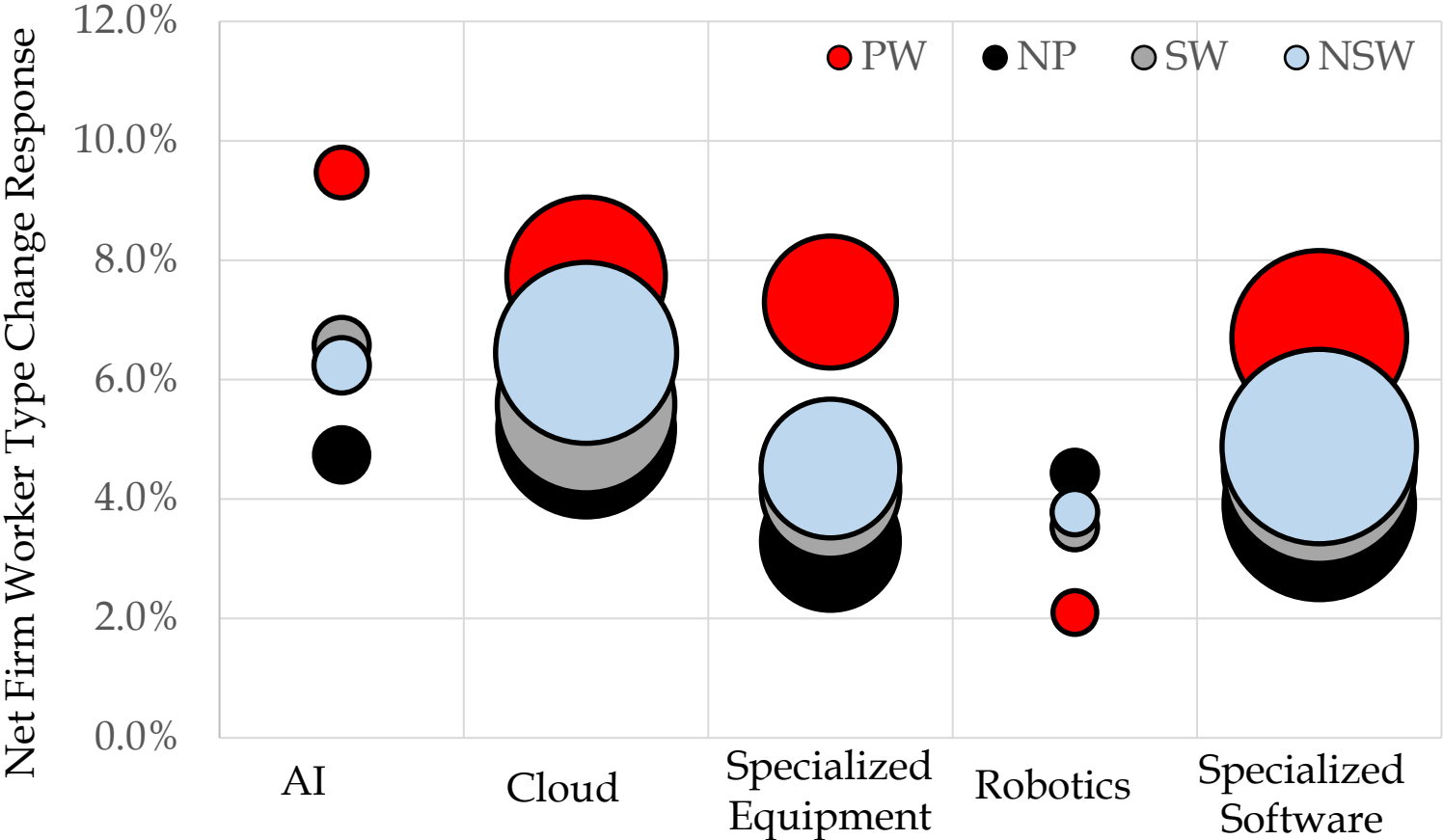
Employment Changes Attributed to Tech

- Majority of adopters do not attribute employment change to tech (~75%)
- More firms attribute employment increases to tech than decreases
- More firms on net attribute employment increases to tech
 - Robotics has smallest net difference



Worker Type Changes (Firm-weighted)

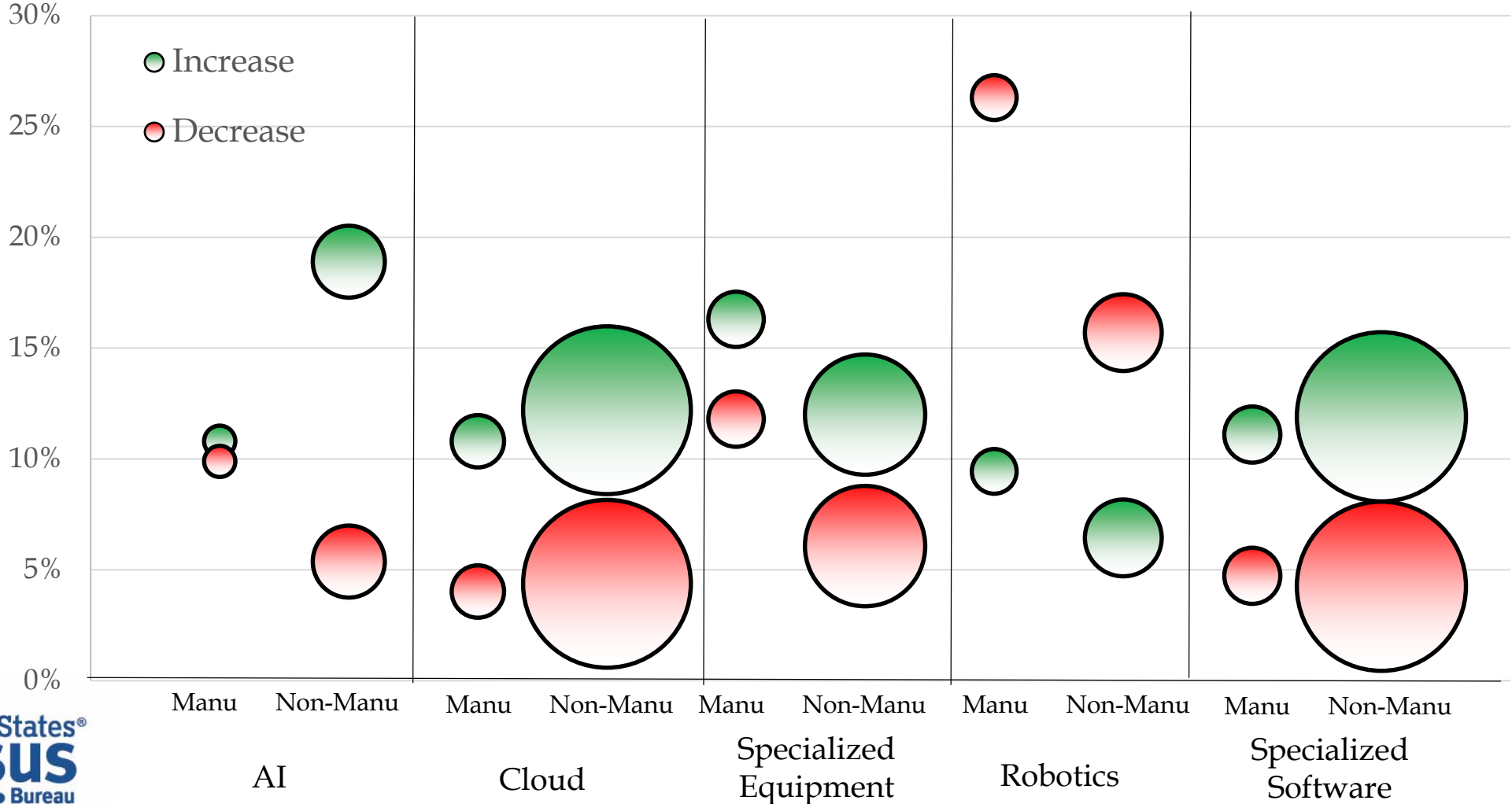
- Firm-weighted changes to worker type show similar patterns but no net negative for production workers



Bubble size corresponds to number of adopters who employ worker type

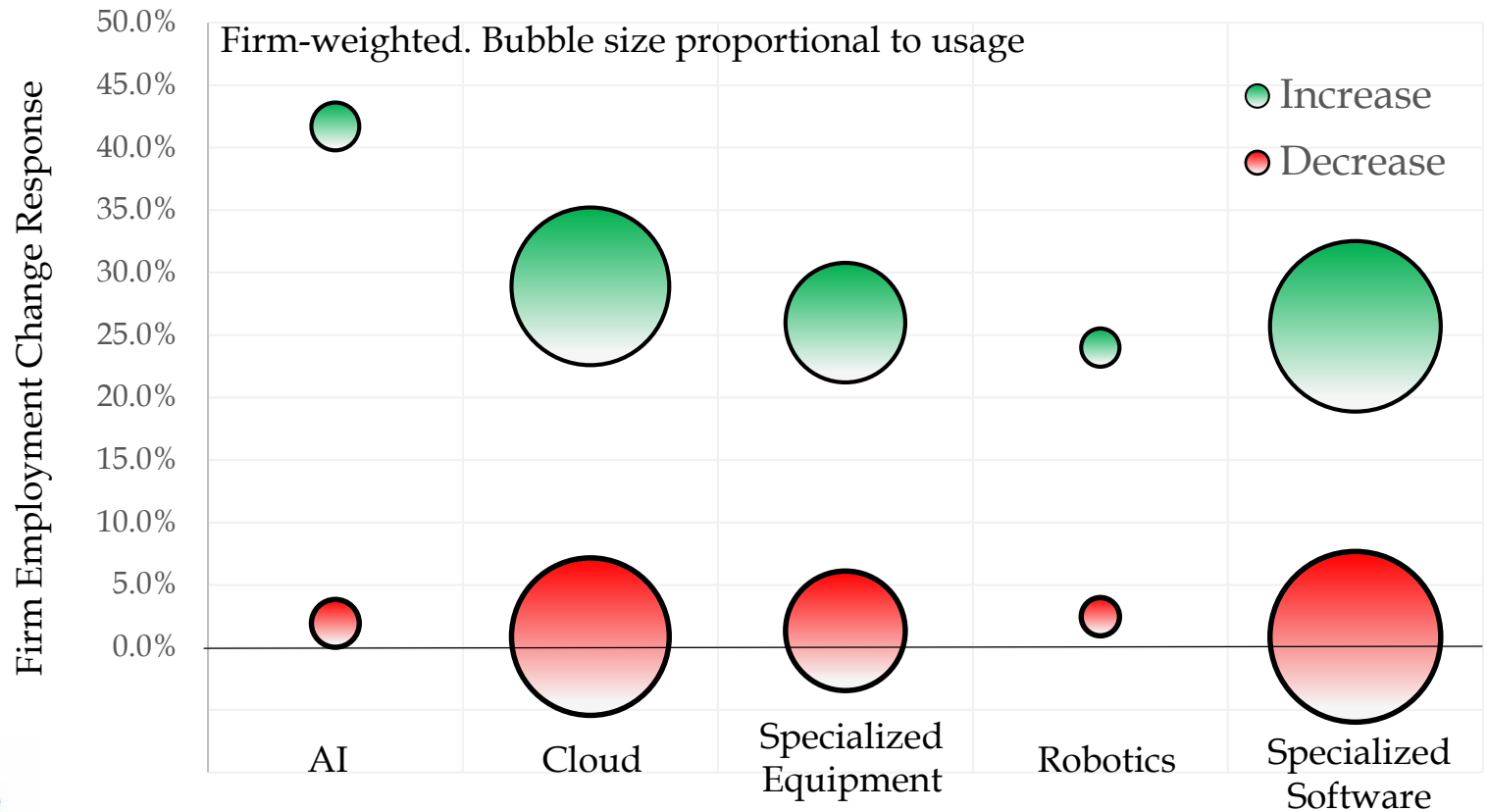
Production Worker Changes by Manufacturing Status

Decline in Production Workers driven by Manufacturing Sector



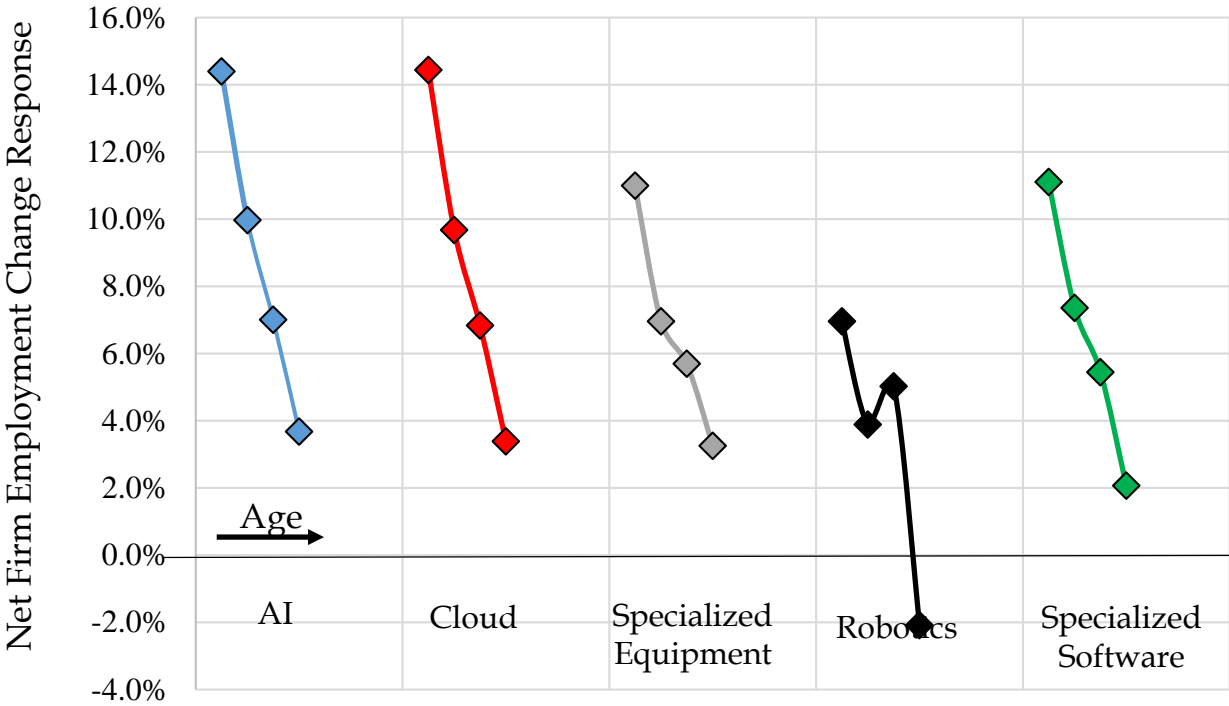
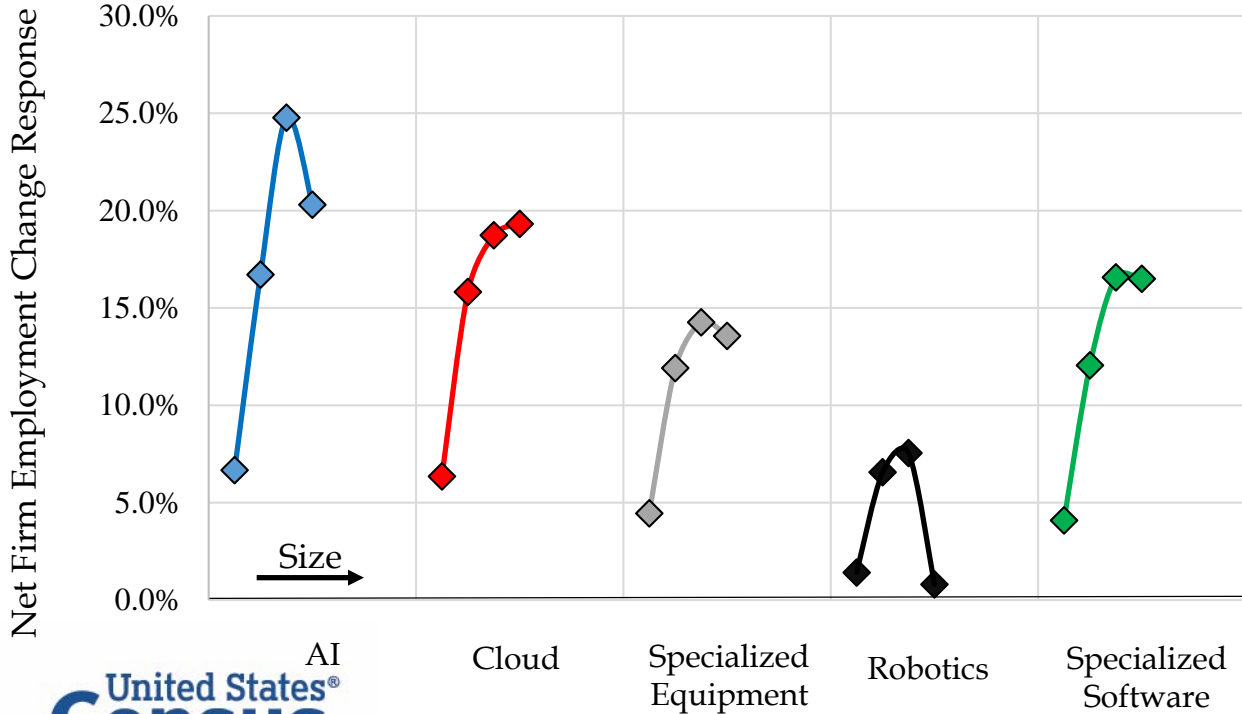
Skill Change by Technology Adoption (Firm-weighted)

- About half of firms attribute changes in skill levels to technology adoption
- Very few firms attribute declining skill levels to technology adoption



Net Employment Change by Size and Age

- Net difference in employment change is positive across all size categories, with lowest difference in Robotics
- Net difference in employment change is declining by age, with oldest firms reporting more employment decreases than increases in Robotics

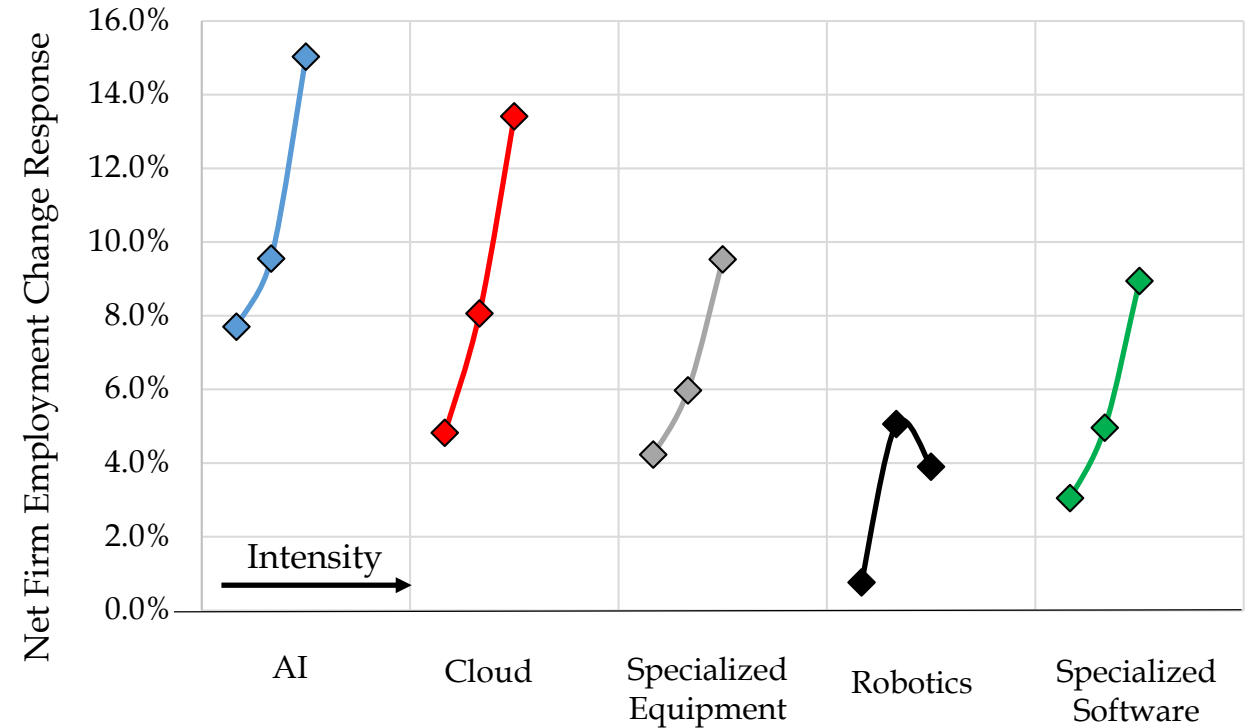
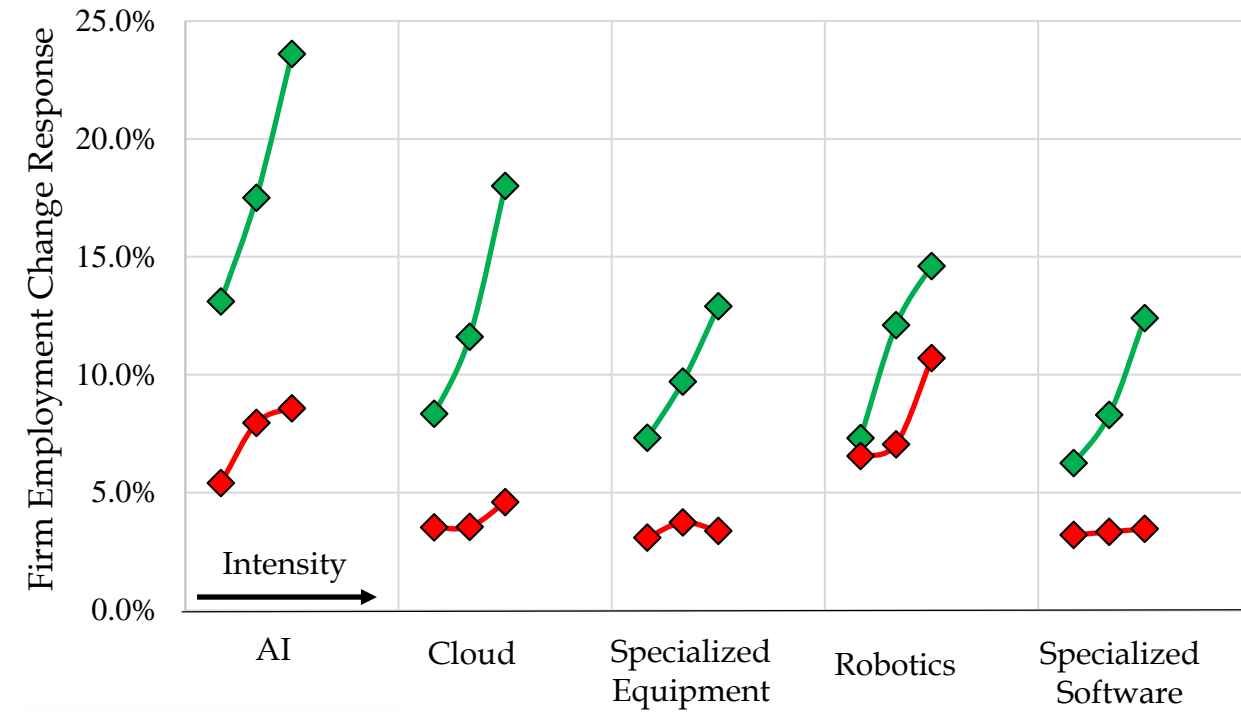


Note: Size categories include: 0-9, 10-49, 50-249 and 250+ employees

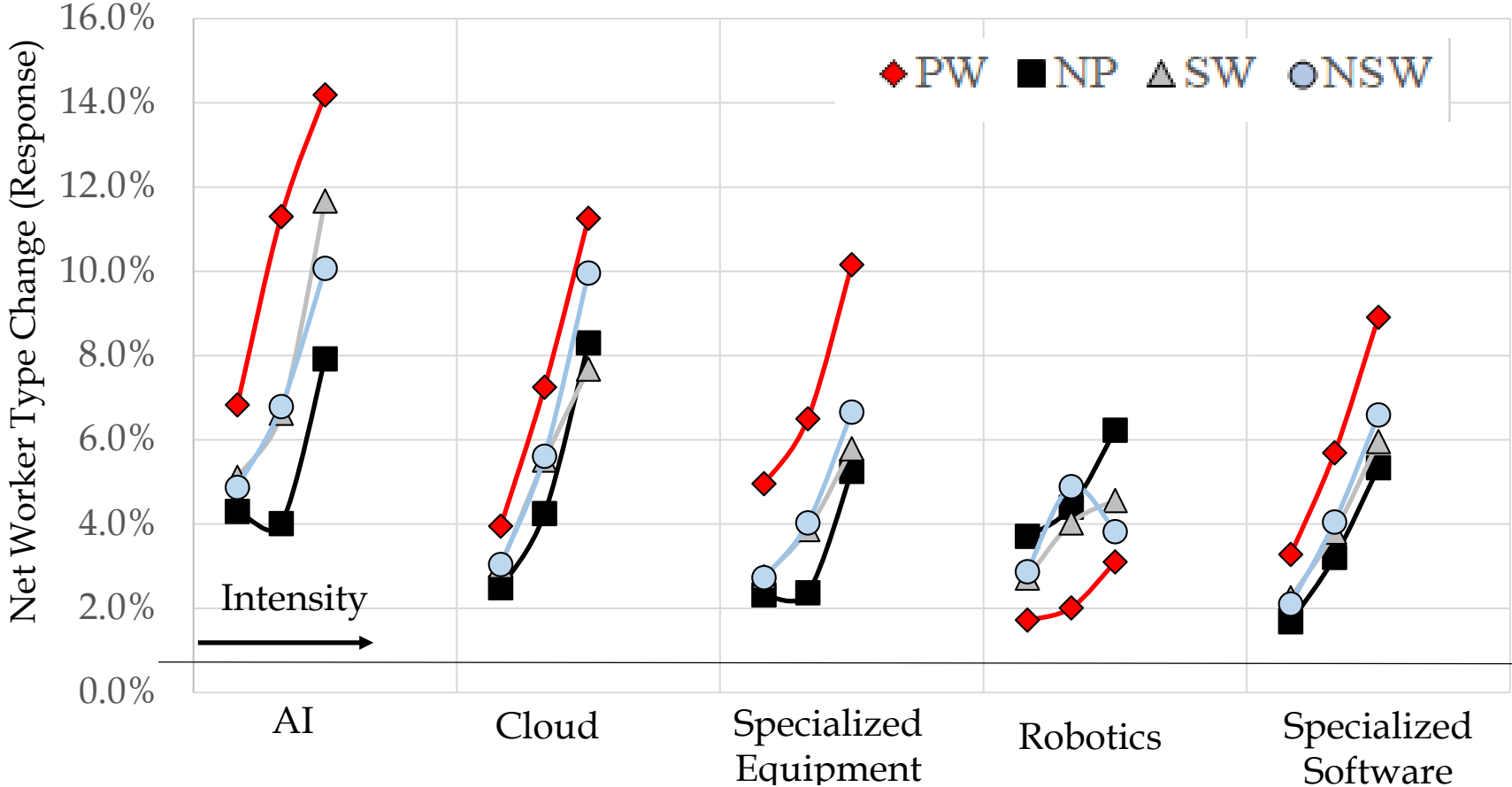
Note: Age categories include: 0-5, 6-10, 11-20 and 21+

Employment Changes by Intensity of Adoption

- Higher technology adoption intensity is associated with higher shares of firms reporting employment increases

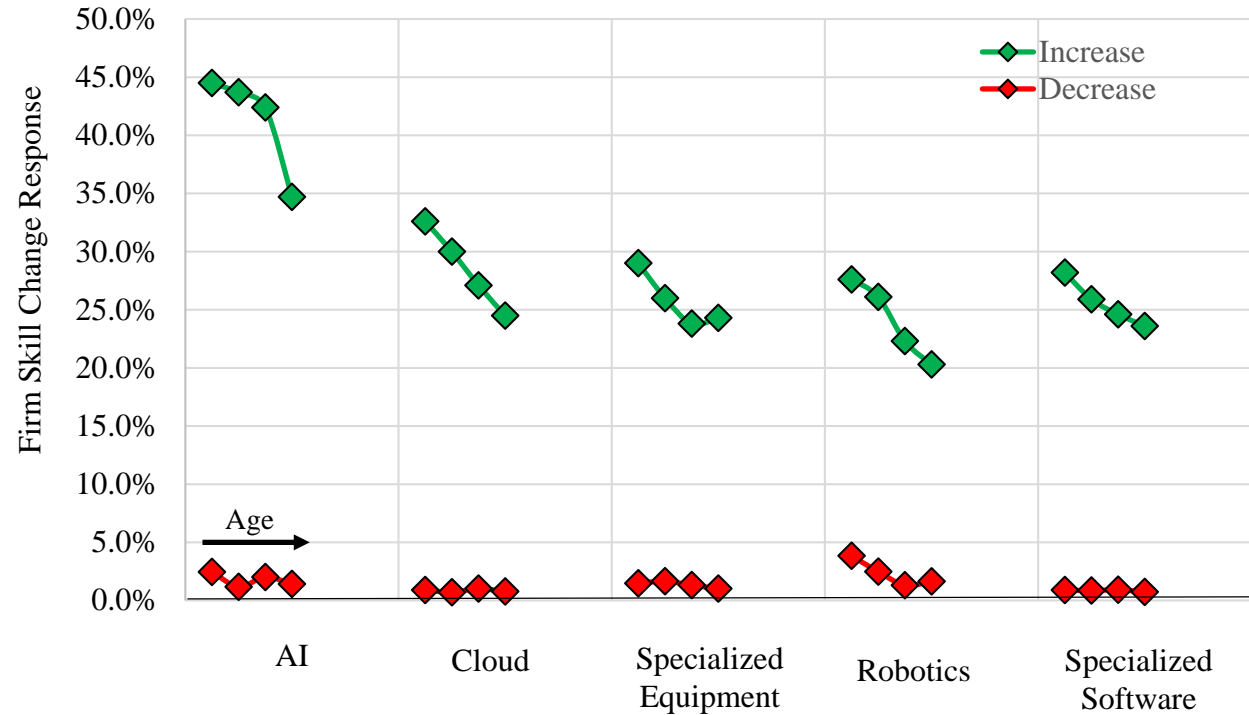
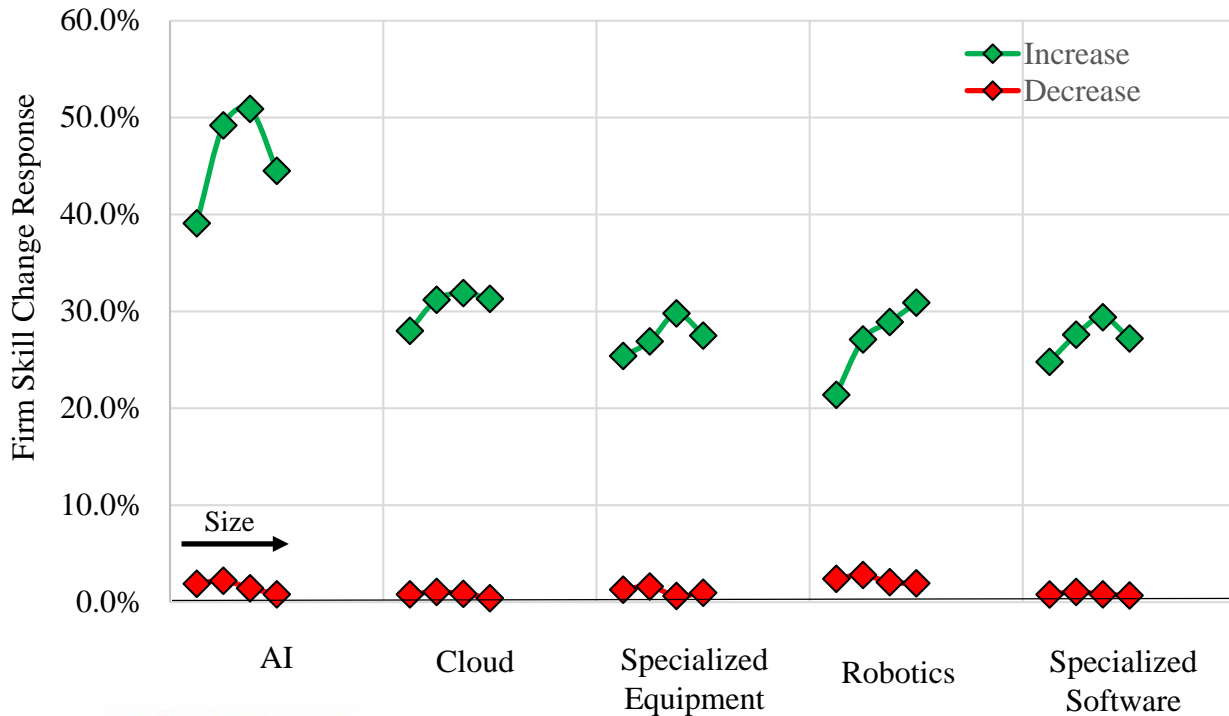


Net Worker Type Change by Intensity of Adoption



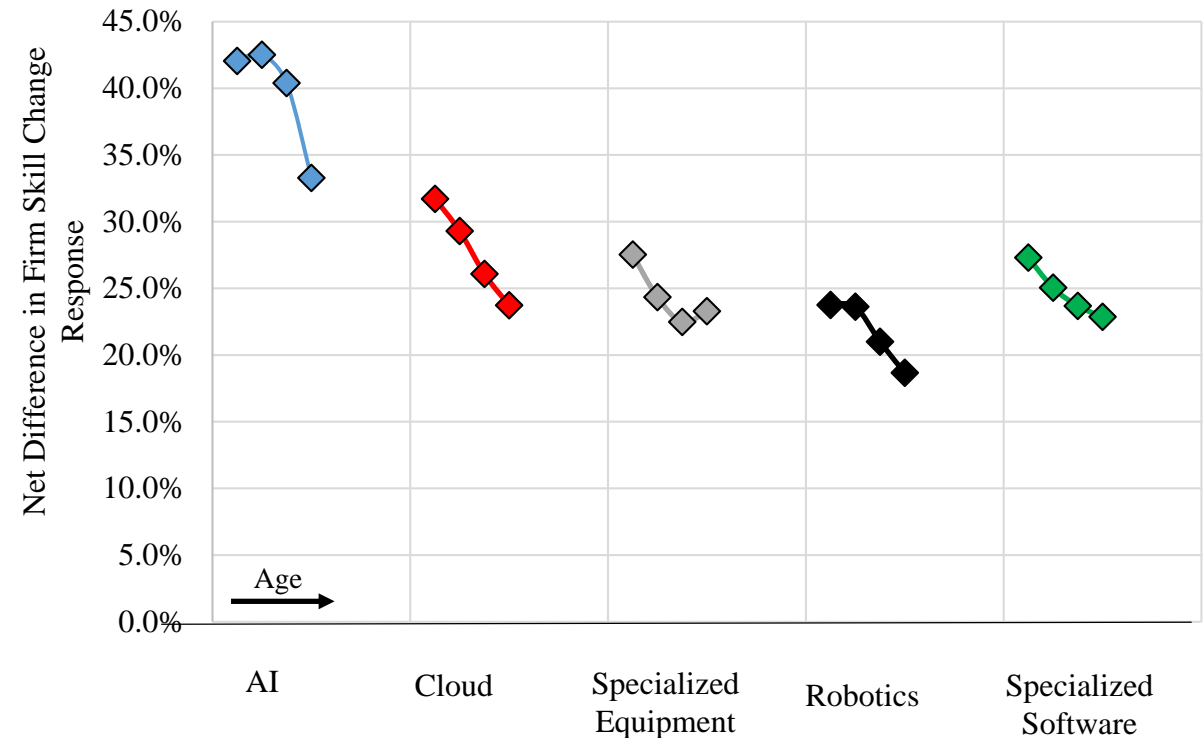
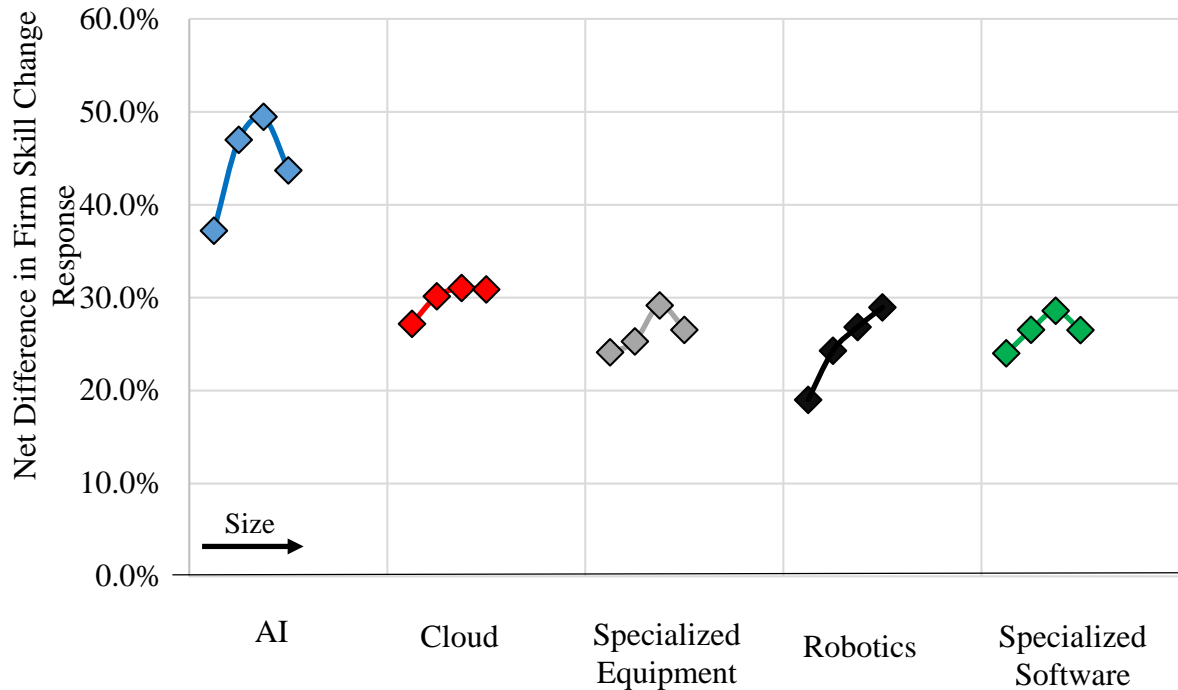
Skill Change by Size and Age

- Larger share of firms report some change to skill
- Size is positively associated with likelihood of reporting Skill increase
- Age is negatively associated with likelihood of reporting Skill increase
- More intense adoption is associated with higher reported Skill increase



Net Skill Change by Size and Age

- Share of firms responding with increased skill increases slightly with size
- Share of firms responding with increased skill decreases with age



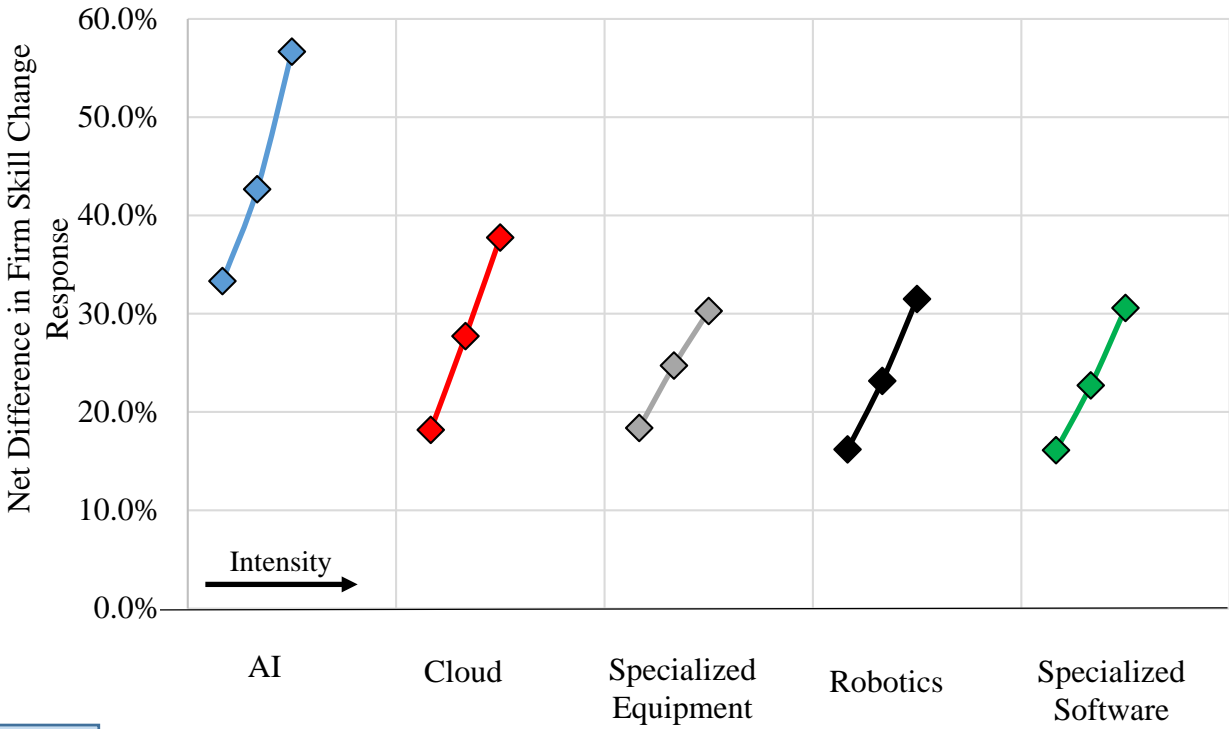
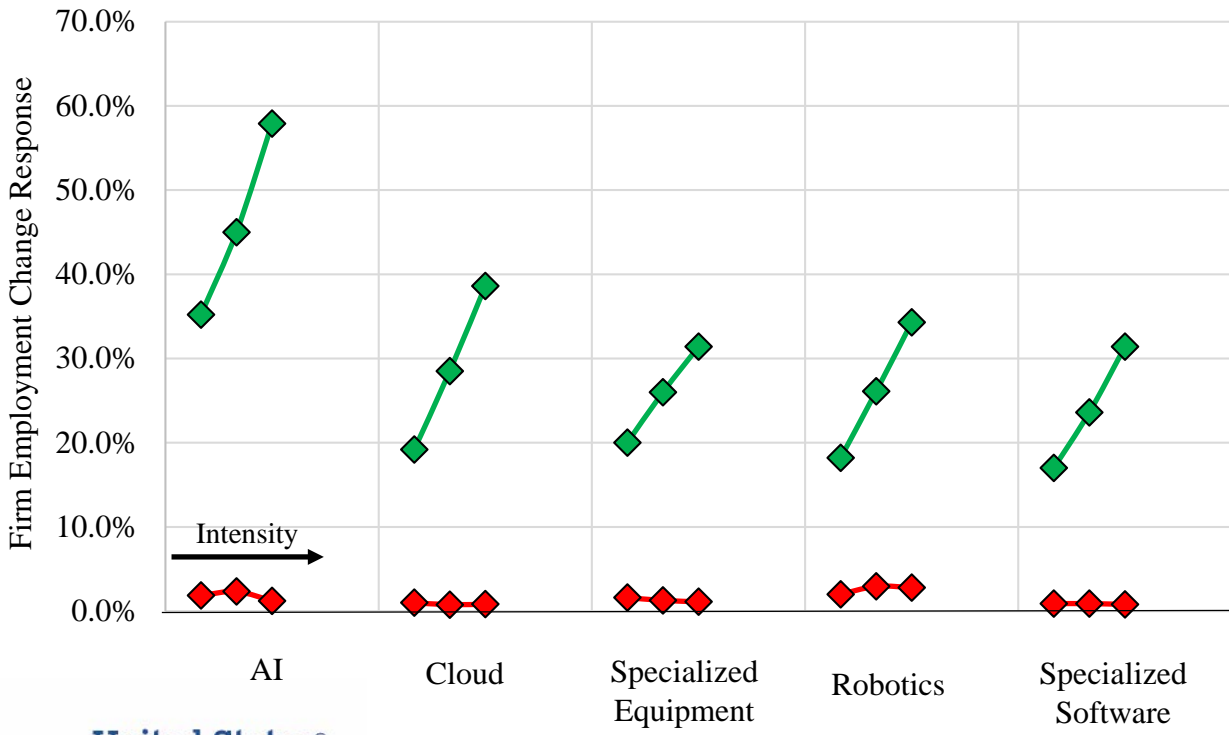
Note: Size categories include: 0-9, 10-49, 50-249 and 250+ employees

Note: Age categories include: 0-5, 6-10, 11-20 and 21+



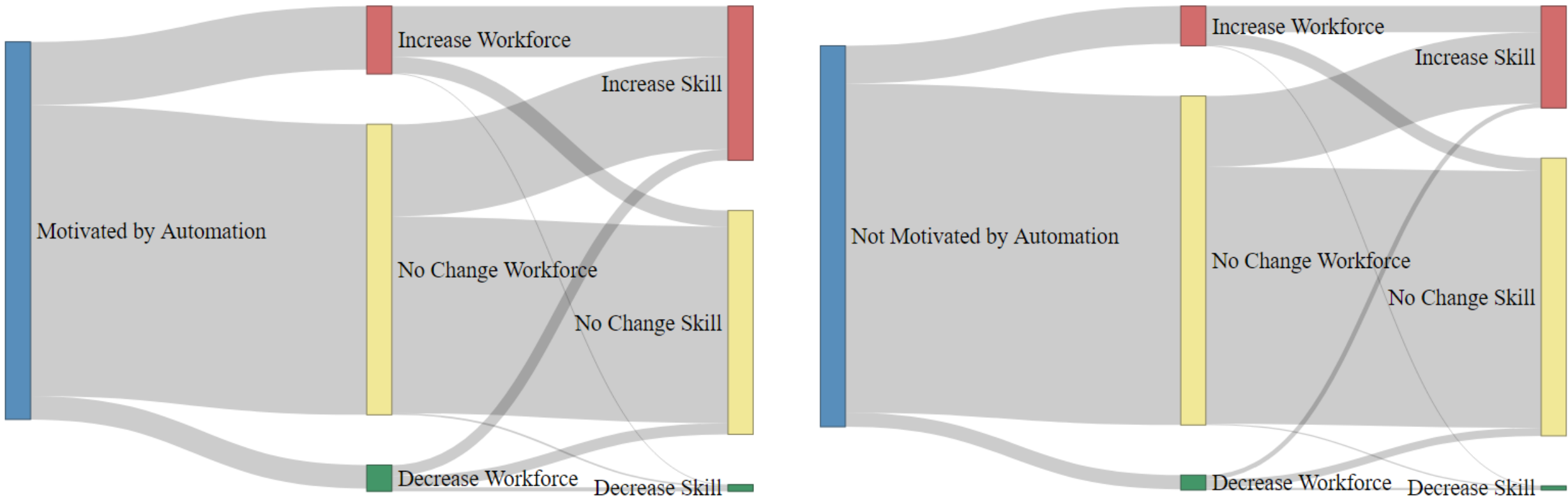
Skill Change by Intensity of Adoption

- As intensity of adoption rises, higher share of firms respond with increasing Skill

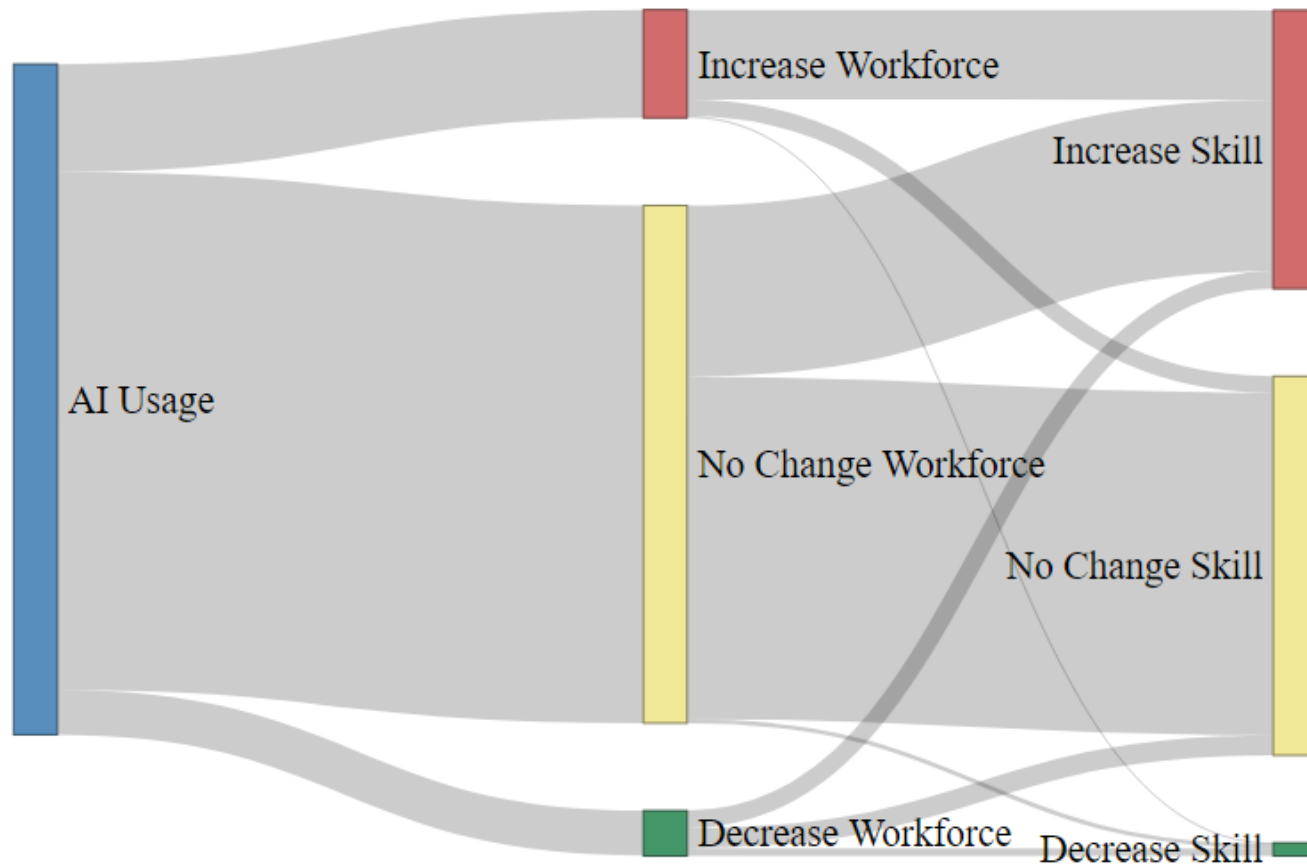


Automation (Firm-weighted)

Similar patterns persist when weighted by firm: Firms motivated by Automation are more likely to report Increase Workforce and Increase Skill

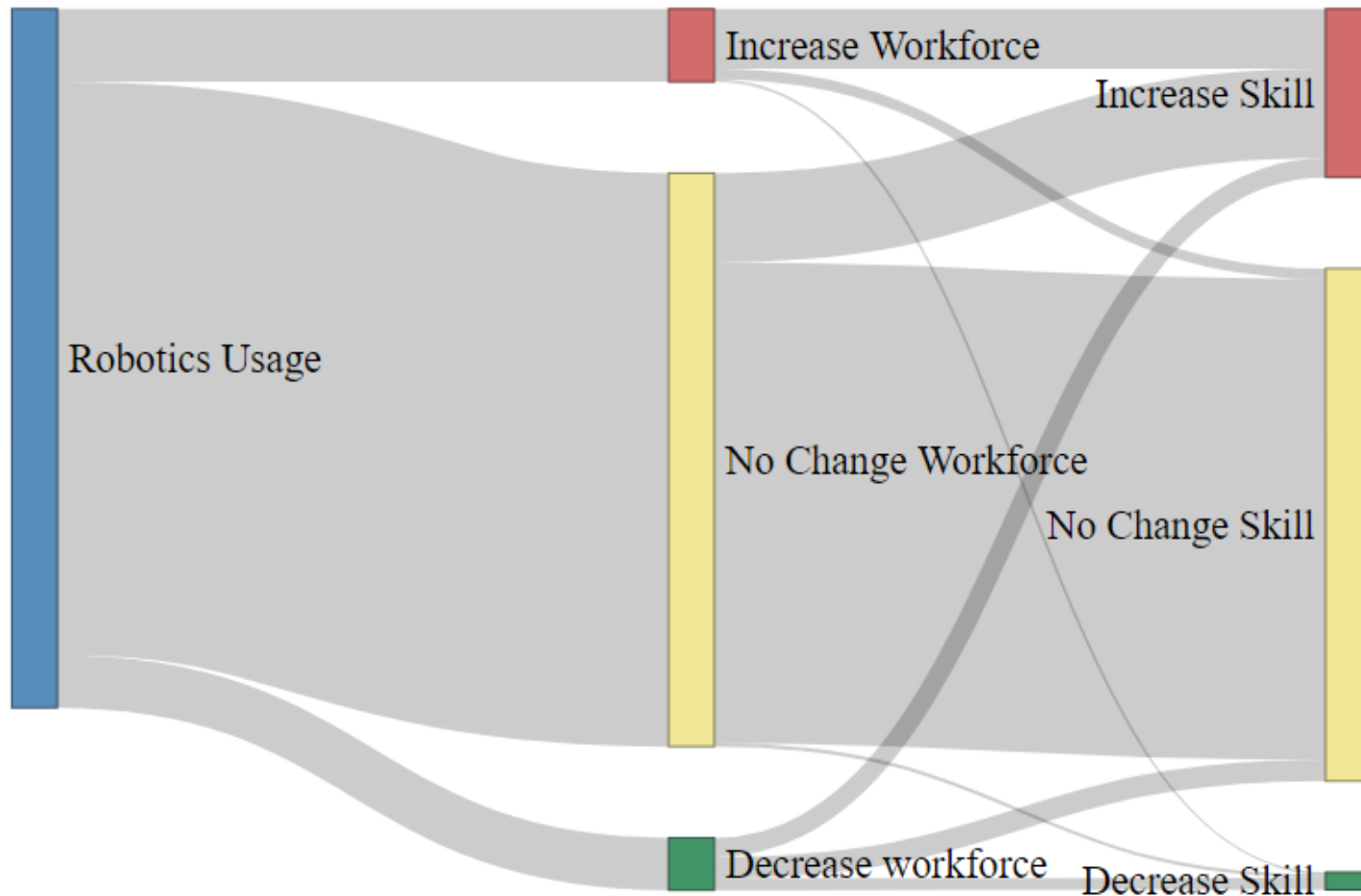


AI Adoption on Employment and Skill Changes (Firm-weighted)



Adoption of AI has mostly led to No Change in Employment, but increase in Skill

Robotics on Employment and Skill (Firm-weighted)

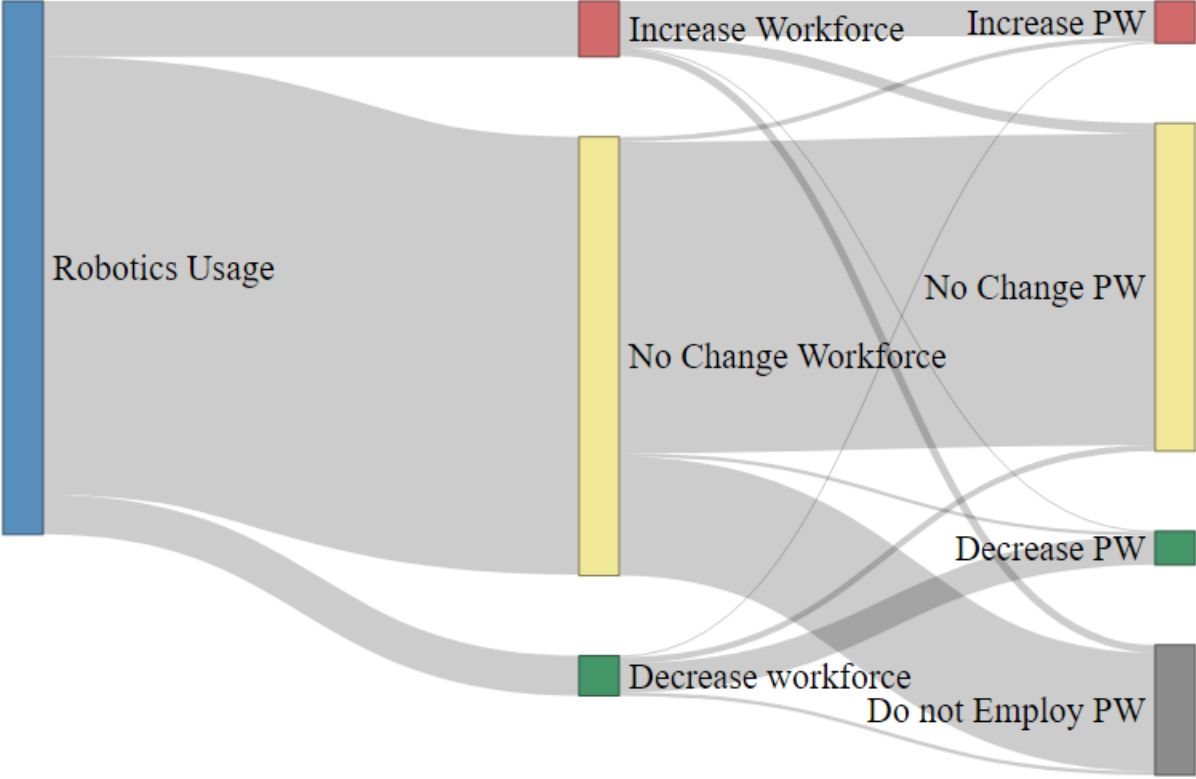


Robotics use is associated with little change in employment and not much change in Skill

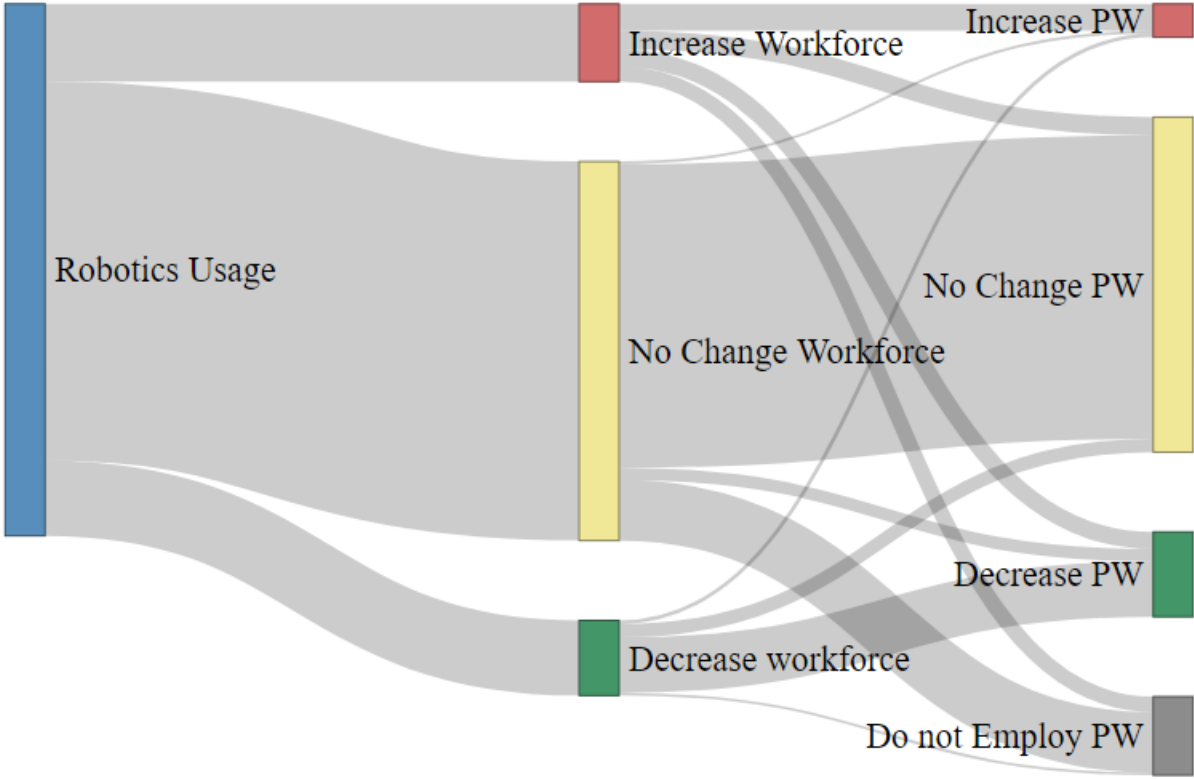
Robotics and Employment and Production Workers

Employment-weighted Robotics employment change highlights how employment decreases are driven by reduction in production workers. Even firms that increase workforce, less than a majority also increase their PW

Firm-weighted



Employment-weighted



Challenges and Next Steps

- “N/A” response option used inappropriately
 - Response option reads “Not applicable, we did not employ [worker type]”
 - Firms respond “N/A” for both production and non-production workers (or both supervisory and non-supervisory workers)
 - Firms respond “N/A” for one technology but not the other
 - *Robustness*: Focus on manufacturing sector for analysis based on worker types
- Non-response
 - Many large, complex firms respond “Don’t Know” or missing for all technologies
 - Individuals responding to survey commonly hold positions such as “financial analyst”
 - *Robustness 1*: Limited telephone follow-up for those with Census account managers
 - *Robustness 2*: Repeat analysis and focus on smaller, less complex firms
- Current weights unfit for longitudinal analysis
 - Much larger sample in Year 1 means longitudinally matched firms received larger weights in Year 2 than in Year 1 (particularly smaller firms)
 - *Solution*: Create our own weights for longitudinally matched sample based on 2017 and 2018 LBD

Challenges and Next Steps (Cont.)

- Causality
 - Assess how combination of firm characteristics (size, age, industry, productivity, payroll per employee, number of establishments, etc...) impact adoption rates
- Validation Exercises
 - Validate robotics usage with firm-level import data
 - Further validation with 2018 ABS

