AUTOMATION AND YOUNG WORKERS' JOB TRAJECTORIES: THE ITALIAN CASE

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MOTIVATIONS

- Profound transformation of labor markets due to automation: Robotics, AI, and digital technologies reshaping job landscapes
- It is relatively straightforward to forecast which jobs might become obsolete due to automation, BUT predicting the new tasks and roles that will emerge as a result is far more challenging (Autor 2022)
- **Theoretical debates**:
  - ✓ Optimistic: Enhanced productivity and new job creation (Nakamura and Zeira, 2023);
  - ✓ Pessimistic: Job displacement and increased inequality (Berg et al., 2018)
- **Recent focus**: Individual worker impacts (Acemoglu et al., 2023); Various forms of automation (Acemoglu et al., 2022)

KEY LITERATURE

- **First generation studies**: Aggregate effects on labor markets

  Country labor market analysis (Graetz and Michaels, 2018)
  Local labor market impacts (Acemoglu and Restrepo, 2020)
  Sector-specific analyses (Dauth et al., 2021; Koch et al., 2021)

- **Second generation**: Individual worker outcomes

  Worker-level data across countries (Acemoglu et al, 2023, Bachmann et al., 2024)
  Task-based analyses (Czaller et al., 2021)

- **Related fields**:

  Firm resilience and automation (Comin et al., 2022)
  Role of labor market institutions (Alesina et al., 2018)

RESEARCH GAPS AND THE AIM OF OUR PAPER

- **Research gaps:**

  - ✓ Limited evidence on how multiple forms of automation affect (young) workers' employment prospects
  - ✓ Insufficient understanding of automation's impact in the context of varying labor market institutions and economic shocks

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We examine the job trajectories of young Italian workers (aged 15-30), investigating the role of automation on their employment prospects

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We assess impact of various automation types on employment probability

AIM OF THE PAPER

- We employ high-quality data from Italy: information on job creation from an **employer-employee administrative dataset** provided by the Italian Ministry of Labor and Social Policies
- Merge administrative and firm survey data (2018Q1-2023Q2)
- Track employment status and pre-shock automation exposure

Key Findings:

- Positive association between automation exposure and employment
- Heterogeneous effects, stronger in larger firms and for permanent contracts
- Evidence of job resilience post-COVID layoff freezing

THE DATASET

Unique employee-employer panel dataset, combining:

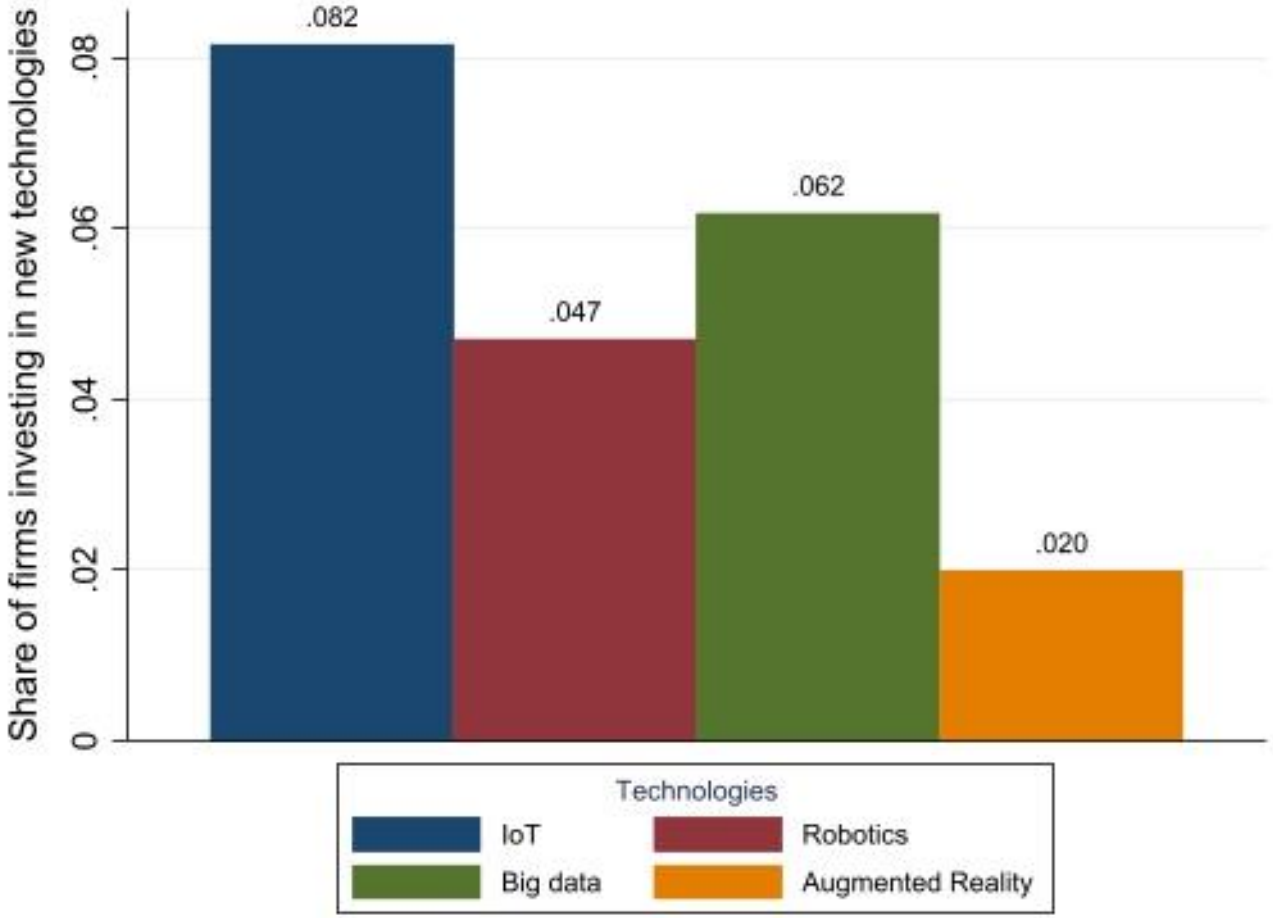
- **COB** (Compulsory Communications System): Administrative job flow data from the Italian Ministry of Labor and Social Policy
- **RIL-2018** (Rilevazione Imprese e Lavoro): Nationally representative firm survey data from INAPP

- **Sample**: 67,709 workers aged 15-30 at the time of exposure, covering 10,902 firms and 1,489,816 quarterly observations (2018Q1-2023Q2)

- **Key variables**: Automation investments (2015-2017) in robotics, Internet of Things (IoT), Big Data, Augmented Reality (AR); Worker- and firm-level characteristics (e.g., gender, education, sector, firm size)

AUTOMATION INVESTMENTS

Share of firms investing in new technologies (2015-2017)



Source: author’s elaborations on RIL-2018 data

EXPOSURE TO AUTOMATION MEASURE

Key variable: **EXPA (Exposure to Automation)**

- Measures whether a worker has been employed by a firm that invested in automation during the period 2015-2017
- **Binary variable** based on employment status and firm's automation investment

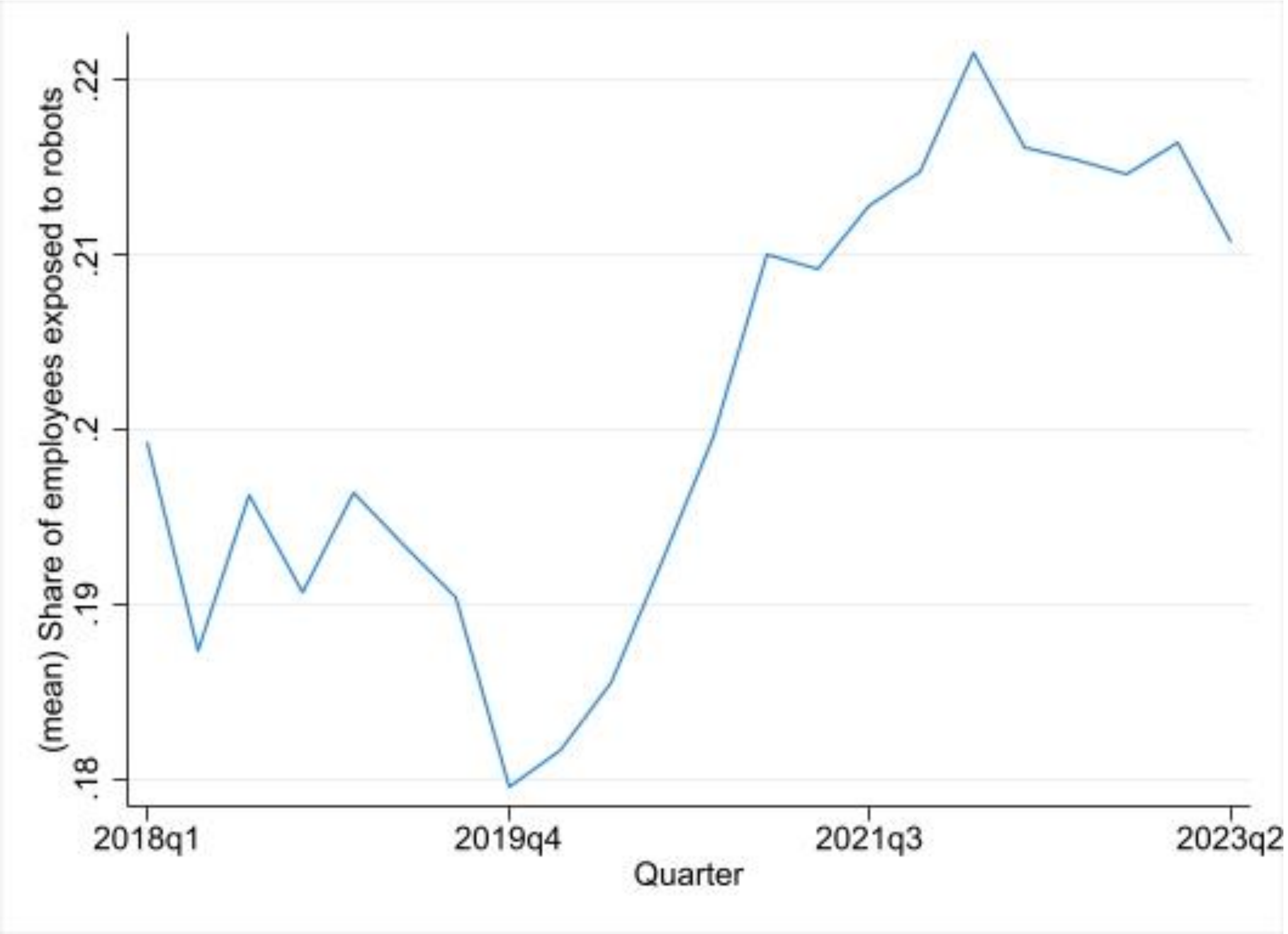
Table 1: Employment and Automation Exposure Combinations

	Type of Firm	
Employment Status	No Automation	Automation
$E_{i,t} = 0$	A: $EXP_A = 0$	B: $EXP_A = 1$
$E_{i,t} = 1$	C: $EXP_A = 0$	D: $EXP_A = 1$

- **EXPA = 1** from the quarter the worker is employed by an automating firm, regardless of subsequent employment status

WORKERS EXPOSED TO ROBOTS

Evolution of the share of employees exposed to robots



Source: author’s elaborations on COB-RIL merged dataset

EMPIRICAL STRATEGY

Dynamic random effects logit model

$$E_{it} = 1\{\alpha_i \beta E_{it-1} + \gamma EXP_{A_{it}} + \delta \mathbf{W}'_i + \zeta \mathbf{F}'_i + \sum_{q=2}^{T} \tau_q \eta_q + \epsilon_{it} > 0\},$$

- E_{it}:the employment status (1 if employed, 0 otherwise)
- EXP_{Ait}: Exposure to automation (robots, IoT, big data, AR)
- W_i: Vector of worker's characteristics
- F_i: vector of firm's characteristics
- η_q: Quarterly dummies
- α_i: Individual random intercepts
- ε_{it}: Error term, type I extreme value distribution

Initial conditions problem: crucial in dynamic models with unobserved effects

- Rabe-Hesketh and Skrondal (2013) strategy (very useful when Heckman strategy is not feasible, as in this work):
  - ✓ Include initial-period explanatory variables as additional regressors

In our case:

- Nature of our sample makes this strategy less relevant:
  - ✓ Young worker cohort (ages 15-30) with limited pre-sample history
  - ✓ Worker- and firm-level characteristics substantially time-invariant
  - ✓ Observation period (2018-2023) follows automation investments (2015-2017)

EMPIRICAL STRATEGY

Initial conditions problem: crucial in dynamic models with unobserved effects

- Our design inherently addresses initial conditions
  - ✓ Automation exposure acts as a "reset point" for employment trajectories
  - ✓ Focus on differential trajectories post-exposure
- **Key features**:
  - ✓ Reduced dependence on unobserved pre-sample conditions
  - ✓ Time-invariant characteristics captured in individual-specific effects
  - ✓ Leverage timing of automation investments preceding observation period
- **Result**: Our design naturally mitigates initial conditions concern without need for additional time-varying regressors

MAIN RESULTS

Table 4: Exposure to Automation: Marginal Effects.

	Dependent variable: Employed							
	a) Robots				b) IoT	c) Big Data	d) AR	e) AL1
EXP_A	0.120***	0.095***	0.095***	0.094***	0.089***	0.098***	0.083***	0.178***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lagged dep. var. (t-1)	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects		✓	✓	✓	✓	✓	✓	✓
Worker-level controls			✓	✓	✓	✓	✓	✓
Firm-level controls				✓	✓	✓	✓	✓
Number of workers	67,504	67,504	67,498	60,751	60,751	60,751	60,751	60,751
Number of observations	1,417,538	1,417,538	1,417,412	1,417,412	1,417,412	1,417,412	1,417,412	1,275,731

Source: Authors' calculations based on COB-RIL2018 merged dataset.

Notes: The table reports the marginal effects of random effect dynamic logit estimates on the probability of being employed when exposed to automation technologies. Worker-level controls include gender, nationality, education level, and macro-region of residence. Firm-level controls encompass firm size and age, sector of activity, (log of) sales per capita, share of workers with different levels of education and occupation, share of employees with temporary contract, managerial's characteristics, and the share of firms with family ownership. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors reported in parentheses.

- The **exposure to automation technologies has a positive and strongly statistically significant impact on employment probability** of young workers
- Once the various levels of controls are included in the models, the EXP_A associated coefficients remain **consistently stable across the estimates and the corresponding type of automation technology**
- Range from 8.3% (in the case of AR, Panel d)) to 9.8% (for Big Data, Panel c)

WHY A POSITIVE EFFECT?

- **Upskilling**
  - ✓ Exposure to automation often requires workers to upgrade skills, increasing their adaptability and value in the labor market (Autor, 2015)
- **Firm Resilience**
  - ✓ Firms with flexible production systems, including automation technologies, were better equipped to handle shifts in demand during crises like the COVID-19 pandemic, reducing the need for layoffs
- **Productivity Gains**
  - ✓ Automation drives productivity improvements, leading to firm growth and an increased demand for labor, which positively impacts employment (Graetz & Michaels, 2018)

EFFECT-HETEROGENEITY ANALYSIS: FIRMS SIZE

Table 5: Exposure to Automation and Firm Size: Marginal Effects.

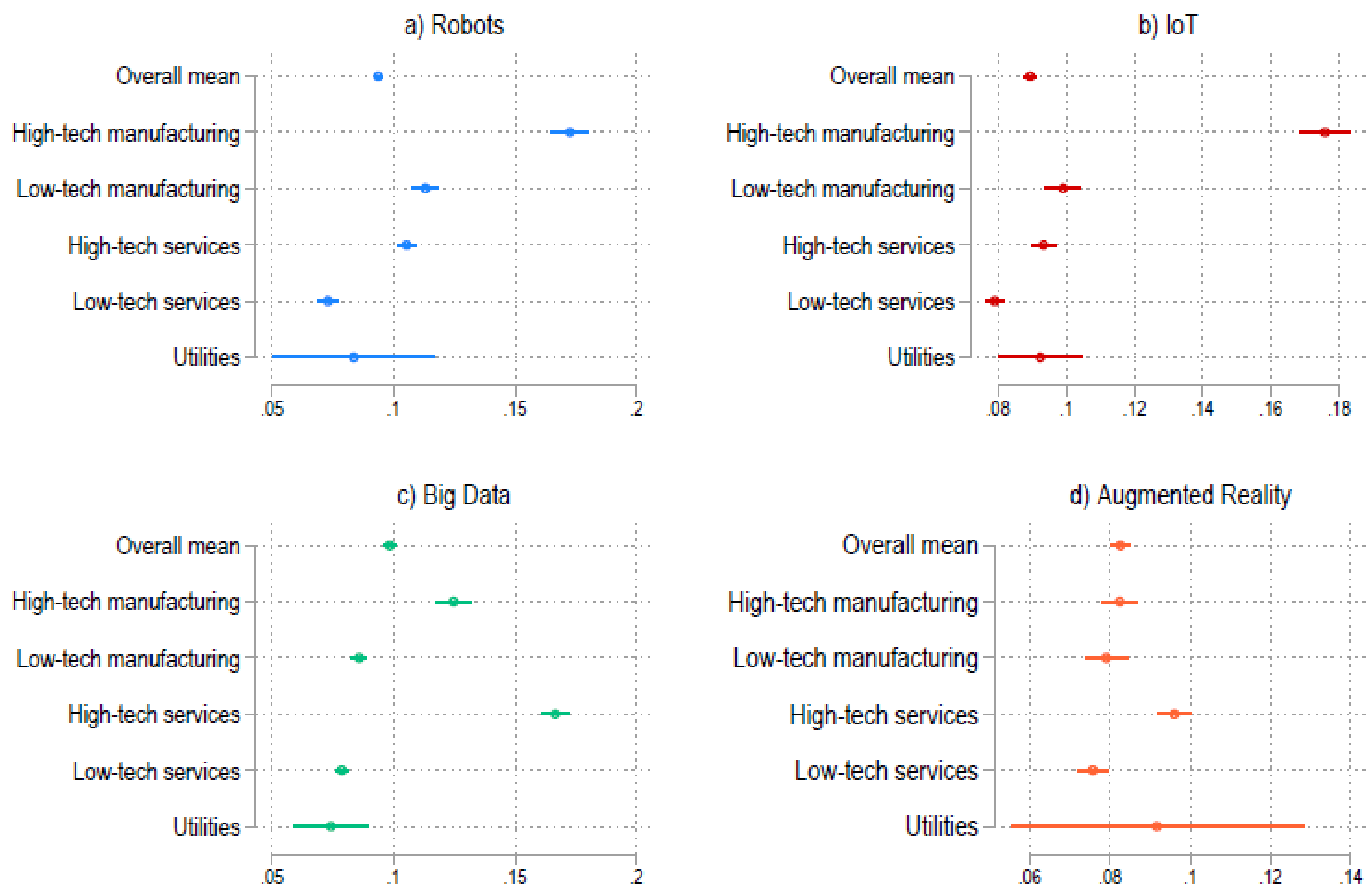
Dependent Variable: Employed				
Firm size ≤ 15 employees				
	Robots	*IoT*	*Big Data*	*AR*
	(1)	(2)	(3)	(4)
EXP_A	0.081***	0.061***	0.061***	0.058***
	(0.001)	(0.005)	(0.005)	(0.009)
Full set of controls	✓	✓	✓	✓
Number of workers	3,295	3,295	3,295	3,295
Number of observations	69,195	69,195	69,195	69,195
Firm size > 15 employees				
	Robots	*IoT*	*Big Data*	*AR*
	(5)	(6)	(7)	(8)
EXP_A	0.094***	0.090***	0.102***	0.083***
	(0.001)	(0.003)	(0.001)	(0.001)
Full set of controls	✓	✓	✓	✓
Number of workers	57,456	57,456	57,456	57,456
Number of observations	1,206,536	1,206,536	1,206,536	1,206,536

Source: Authors' calculations based on COB-RIL2018 merged dataset.
Notes: The table reports the marginal effects of random effect dynamic logit estimates on the probability of being employed when exposed to automation technologies. Lagged-dependent variable, time fixed effects, worker- and firm-level controls are included in all estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors reported in parentheses.

- The effect of exposure is **more pronounced in larger firms** (bottom panel)
- Differences ranging from 1.3% to 4.1% (i.e., in the case of robots and big data)
- The exposure to investments in robots appears to be the most homogeneous treatment by firm size

EFFECT-HETEROGENEITY ANALYSIS: FIRMS SECTOR

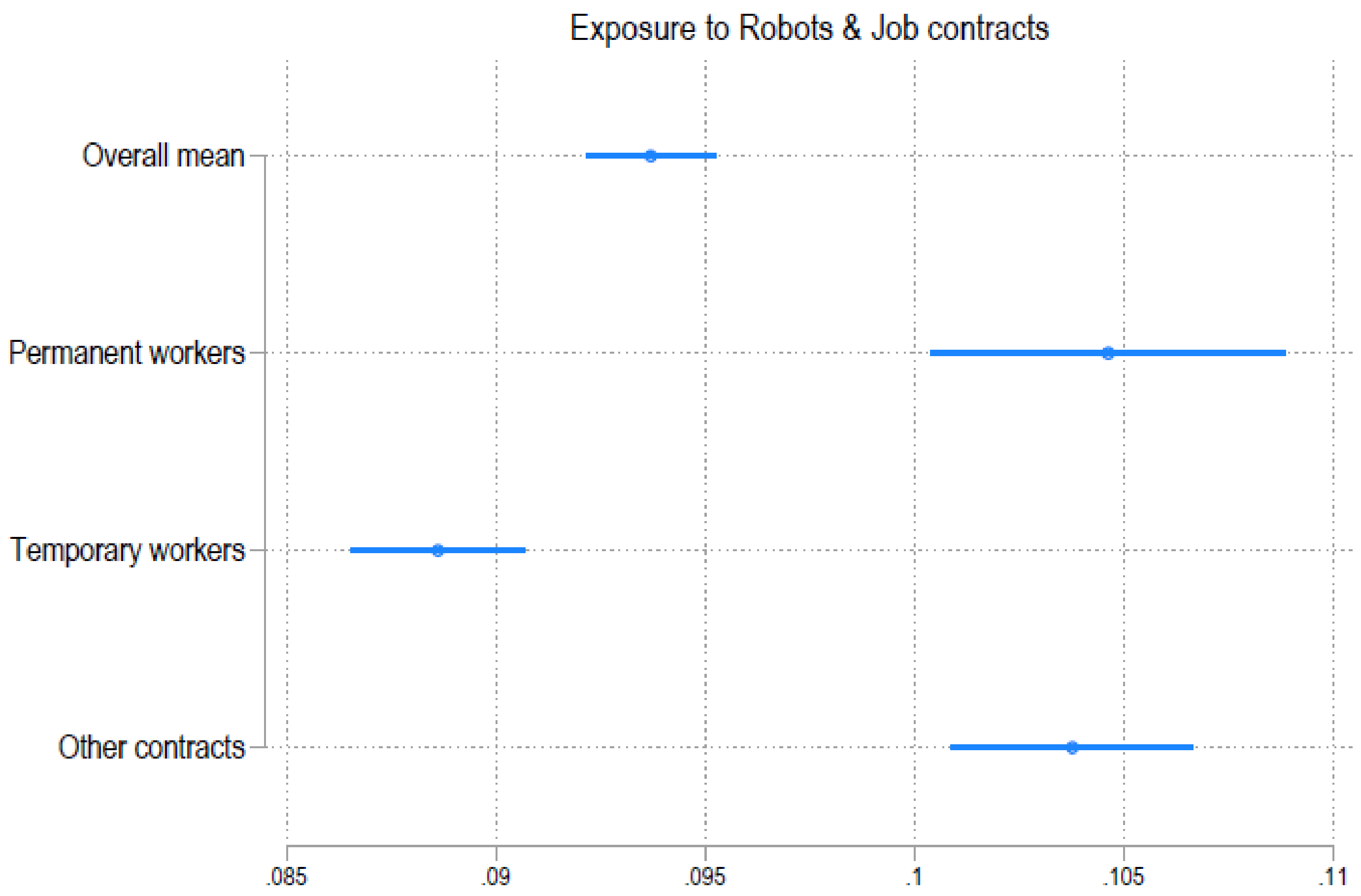
Figure 8: Automation and Employment: Sectoral Heterogeneity Analysis.



- Notable differences in the marginal effects of automation technologies across sectors
- Workers operating in **high-tech manufacturing** significantly **increase the probability of staying employed** when exposed to **robots and IoT**
- **Big Data** correlates with **higher employment retention probabilities** in high-tech manufacturing and service sectors
- **AR** does not indicate considerable deviations from the overall mean, implying a **more uniform effect across different sectors**

EFFECT-HETEROGENEITY ANALYSIS: CONTRACT TYPES

Figure 6: Automation and Employment: Differences by job/contract stability.

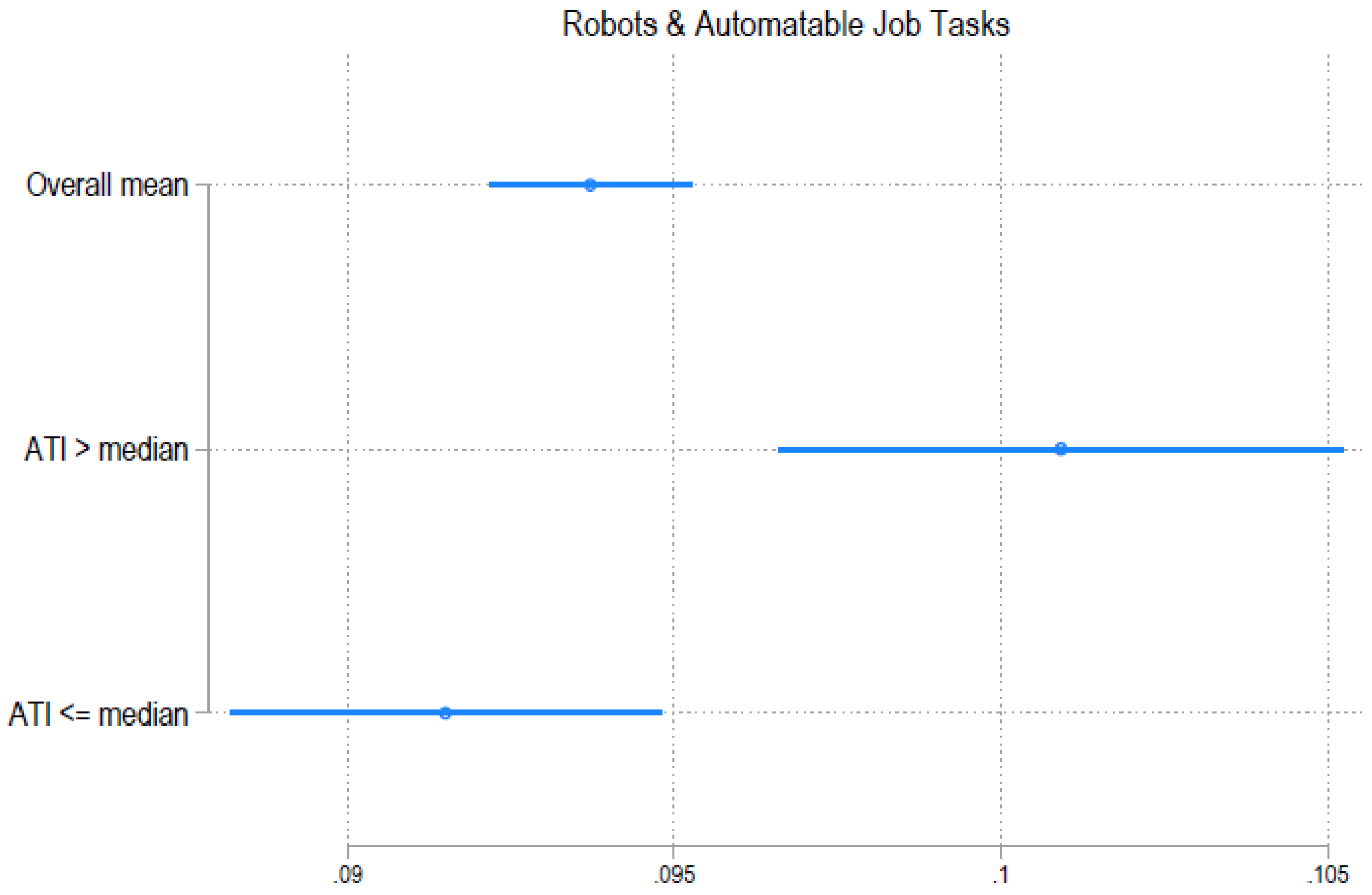


- Temporary workers, when exposed to robots, experience a **relatively lower probability of maintaining employment**, approximately **one fifth lower** compared to permanent (and other) workers

- The **positive effects of automation**, such as the complementarity and upskilling of workers, a**re less pronounced for those in less secure job positions**

EXPOSURE AND VULNERABILITY OF WORKERS QUALIFICATIONS

Figure 7: Automation and Employment:
Differences by task content of automatable qualifications.



- Workers with higher levels of automatable tasks benefit more from exposure to automation
- Roughly 10% greater compared to jobs with automatable tasks below the median
- Restrepo (2023): young workers can exhibit a higher ability to reallocate and mitigate the adverse impacts of automation. Firms investing in automation often also invest in reskilling programs to help workers adapt to new technologies
- Workers with automatable tasks are transitioned into roles that involve supervising and managing automated systems enhancing their employment security

CONCLUSIONS

- This study investigated the impact of automation technologies (robots, IoT, big data, AR) on young workers' job trajectories in Italy
- A unique employee-employer dataset was used, covering 67,709 workers and over 1.4 million quarterly observations (2018Q1-2023Q2)
- **Main results**
  - ✓ Automation exposure has a significant **positive effect on employment probability**
  - ✓ **Larger firms and workers with permanent contracts benefit the most from automation**
  - ✓ **Remarkable sectoral heterogeneity**

- **Ongoing Research:** Analyzing the **impact of automation on wage inequality and job quality**
- **Future Research**
  - ✓ Investigating the interaction between automation and different types of labor market institutions across countries
  - ✓ Exploring the role of digital transformation beyond automation, including AI and machine learning, on labor market outcomes

THANKS FOR YOUR ATTENTION

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