

# New technologies, firm performances and work

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24 May 2022

Istituto Nazionale per l'Analisi delle Politiche Pubbliche (INAPP)  
Roma, via Corso d'Italia 33  
INAPP Seminars

## Motivation (digital techs, productivity, sales)

1. Investments in digital technologies are expected to have positive effects on firm performance (Syverson, 2011);
  - ▶ Improving business processes toward customized productions (Bartel, et al., 2007);
  - ▶ Automating routine tasks and reducing costs of interactions with suppliers and customers (Akerman et al., 2013);
  - ▶ Upgrading internal knowledge-base through patents in digital techs (Grinza et al., 2019);
  - ▶ Advanced technologies allow firms to produce in a more capital-intensive way, by relying more on specialized equipment and software and less on labor + lower employment of less-skilled workers/ increase the hiring of more-skilled workers (Acemoglu et al., 2022)
2. Empirical evidence at the industry and firm levels is scant (lack of appropriate microdata);
3. Not univocally reflect the revolutionary expectations placed on these technologies (Acemoglu et al., 2014; DeStefano et al., 2018; Cette et al., 2017; Gal et al., 2019)
4. Links between adoption of digital technologies and productivity are complex.

## Motivation (digital techs, productivity and wages)

1. Discrepancy between digitalization and effective productivity gains, "modern productivity paradox" (Acemoglu et al., 2014; Brynjolfsson et al., 2017), lack of:
  - ▶ Complementarity with firms' complex set of capabilities (Dosi et al, 2000; Winter, 2003), including managerial / organizational practices, adaptive routines, absorptive capacity (Cohen and Levithal, 1990), or financial structure and organization.
2. At an aggregate level, slowdown of labour productivity growth and a decoupling between productivity and wage growth (OECD, 2015; 2018; IMF, 2017);
3. Dauth et al. (2017) find different effects depending on workers' skills and tasks: positive effect on high-skilled workers, negative for lower and medium-skilled workers' employed in machine-operating occupations.

# Research questions

- ▶ Do firms investing in I4.0 realize some productivity gains and improve their performance?
- ▶ If so, are these gains redistributed to workers through wage growth?
  - ▶ Does the introduction of I4.0 techs differently affect labour productivity, average sales and wages by firm size, sector of activity and firm age?
- ▶ How do digital investments affect firms having heterogeneous performances in terms of labour productivity, wages and revenues?
- ▶ Can digital techs facilitate the convergence of low-productive/low-paying firms towards high-productive paths?

# Data

- ▶ Merge between 2 main sources of data:
  1. **Rilevazione Imprese e Lavoro (RIL)** conducted by INAPP in 2010, 2015 and 2018 on a representative sample of partnerships and limited liability firms:
    - ▶ Each wave of the survey covers over 25000 firms operating in non-agricultural private sector;
    - ▶ A subsample of the included firms (around 40%) is followed over time, making the RIL dataset partially panel over the period under study;
    - ▶ The V wave of the RIL-INAPP survey included a new set of questions collecting information on the introduction of new digital technologies;
  2. **ORBIS archive** provided by Bureau Van Dijk for the period 2010-2018:
    - ▶ The ORBIS data offers comprehensive information on the balance sheets of almost all the Italian companies operating in the private sector;
    - ▶ The merged dataset contains yearly values of financial variables such as revenues, added value, net profits, book value of physical capital, total wage bill and raw-material expenditures.

## Data

- ▶ The V wave of the RIL-INAPP survey includes a new set of questions collecting information on the introduction of **new digital technologies**:
  - ▶ In the section 'Innovation, Internationalization, Extension of markets', a specific question was added on investments in new technologies over the period 2015-2017: "In the period 2015-2017 did the firm invest in new technologies?"
  - ▶ Although multiple answers are allowed, we adopt a **dichotomous measure of Industry 4.0**: a variable that is equal to 1 if a firm has invested in at least one specific I4.0 tech over the period 2015-2017, 0 otherwise.
- ▶ The final longitudinal RIL-ORBIS sample consists of approximately 3000 firm-year observations over 2010-2018 (after excluding firms with less than 5 employees and firms with missing information for the key variables).
- ▶ Outcome variables: **labour productivity** (value added per employee), **sales** (average sales per employee) and **wages** (total labour cost per employee).

# Empirical strategy

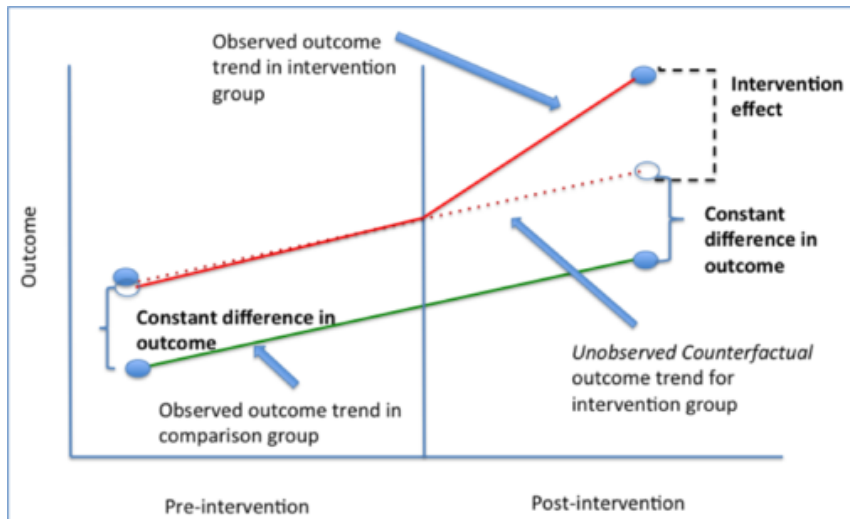
$$Y_{i,t} = \alpha + \beta_1 I_{4.0i} + \beta_2 t + \gamma M_{i,t} + \delta W_{i,t} + \lambda F_{i,t} + \epsilon_{i,t}$$

$$Y_{i,t} = \alpha + \beta_1 I_{4.0i} + \beta_2 t + \beta_3 I_{4.0i} \times t + \gamma M_{i,t} + \delta W_{i,t} + \lambda F_{i,t} + \mu_i + \epsilon_{i,t}$$

$$T = [2010, 2014/2015, 2018]$$

- ▶  $Y_{i,t}$  indicates alternatively log of labour productivity, average wages, average sales for each firm  $i$  at year  $t$  ;
- ▶  $I_{4.0i}$  is a dummy equal to 1 whether the firm has invested in at least one technology among Internet of things (IoT), Robotics, Big data analytic, Augmented reality and Cybersecurity introduced over 2015-2017, 0 otherwise;
- ▶  $M_{i,t}$  includes managerial and corporate governance characteristics;
- ▶  $W_{i,t}$  represents the workforce composition;
- ▶  $F_{i,t}$  is a rich set of firms' productive characteristics, geographical location and sectoral specialization;
- ▶  $t$  is a time indicator;
- ▶  $\mu$  firm fixed-effects capturing time invariant unobserved heterogeneity;
- ▶  $\epsilon_{i,t}$  is the idiosyncratic error term (clustered standard error by firm);
- ▶ Pooled OLS and Fixed effects (FE);
- ▶ Heterogeneity by firm size, sector of activity and firm age.

# Difference-in-Difference estimation, graphical explanation





# Main Results

**Table:** Diff-in-diff labour productivity, wage and sales per employee

	Labour productivity		Average wage		Sales per employee	
	OLS	DIFF-FE	OLS	DIFF-FE	OLS	DIFF FE
Ind 4.0	0.058*** [0.019]		0.019* [0.012]		0.041* [0.027]	
Ind 4.0*year 2018		0.051** [0.020]		0.018* [0.011]		0.048** [0.021]
Ind 4.0*year 2014		0.027 [0.019]		-0.009 [0.011]		0.014 [0.018]
year 2018	-0.023 [0.016]	0.015 [0.017]	-0.009 [0.010]	0.052*** [0.010]	-0.02 [0.023]	-0.036* [0.020]
year 2014	-0.035*** [0.011]	-0.02 [0.015]	-0.015** [0.007]	0.028*** [0.009]	-0.043*** [0.014]	-0.042*** [0.015]
Management ch.	Yes	Yes	Yes	Yes	Yes	Yes
Workforce ch.	Yes	Yes	Yes	Yes	Yes	Yes
Firms ch.	Yes	Yes	Yes	Yes	Yes	Yes
Constant	9.853*** [0.088]	9.778*** [0.189]	10.048*** [0.064]	10.005*** [0.130]	10.528*** [0.131]	11.048*** [0.243]
N of Obs	6971	6963	7251	7240	7244	7244
R2	0.378	0.105	0.455	0.183	0.421	0.104

Source: Longitudinal sample RIL-Orbis. Note: Managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects.

# Results: Heterogeneity of effects by firm size (I)

**Table:** Diff-in-diff **labour productivity** by firm size

	Labour productivity			
	n of employees <50		n of employees >49	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	0.070*** [0.023]		0.038 [0.033]	
Ind 4.0*year 2018		0.066*** [0.024]		0.029 [0.035]
Ind 4.0*year 2014		0.033 [0.021]		0.067 [0.047]
year 2018	-0.016 [0.019]	0.015 [0.02]	-0.023 [0.032]	0.032 [0.031]
year 2014	-0.031** [0.014]	-0.006 [0.016]	-0.039* [0.023]	-0.063 [0.045]
other controls	Yes	Yes	Yes	Yes
constant	10.069*** [0.097]	10.110*** [0.184]	9.467*** [0.157]	9.722*** [0.328]
Obs	4873	4873	2090	2090
R2	0.32	0.07	0.49	0.138

Source: longitudinal sample RIL-Orbis. Note: controls include managerial and corporate governance characteristics, workforce composition, firms' productive characteristics, sectors of activity, nuts 2 regions, industrial relations

## Results: Heterogeneity of effects by firm size (II)

**Table:** Diff-in-diff **wage** by firm size

	Average wage			
	n of employees <50		n of employees >49	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	0.031** [0.014]		-0.01 [0.020]	
Ind 4.0*year 2018		0.023* [0.014]		-0.004 [0.018]
Ind 4.0*year 2014		-0.011 [0.013]		0.014 [0.019]
year 2018	-0.019 [0.012]	0.044*** [0.012]	0.027 [0.021]	0.075*** [0.018]
year 2014	-0.01 [0.009]	0.034*** [0.01]	-0.012 [0.012]	0.005 [0.017]
other controls	Yes	Yes	Yes	Yes
constant	10.118*** [0.071]	10.006*** [0.134]	10.047*** [0.125]	10.163*** [0.175]
Obs	5105	5105	2135	2135
R2	0.378	0.126	0.613	0.276

Source: longitudinal sample RIL-Orbis. Note: controls include managerial and corporate governance characteristics, workforce composition, firms' productive characteristics, sectors of activity, nuts 2 regions, industrial relations

## Results: Heterogeneity of effects by firm size (III)

**Table: Diff-in-diff sales by firm size**

	n of employees <50		n of employees >49	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	0.069** [0.032]		0.001 [0.054]	
Ind 4.0*year 2018		0.067*** [0.025]		0.006 [0.035]
Ind 4.0*year 2014		0.021 [0.020]		0.002 [0.034]
2018	-0.018 [0.026]	-0.039* [0.020]	0 [0.051]	-0.012 [0.037]
2014	-0.046*** [0.017]	-0.043*** [0.016]	-0.019 [0.027]	-0.022 [0.028]
management ch	Yes	Yes	Yes	Yes
workforce ch	Yes	Yes	Yes	Yes
firms ch	Yes	Yes	Yes	Yes
constant	10.826*** [0.141]	11.277*** [0.231]	10.059*** [0.258]	9.995*** [0.443]
Obs	5106	5106	2138	2138
R2	0.376	0.053	0.522	0.129

Source: longitudinal sample RIL-Orbis. Note: Managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects.

# Results: Heterogeneity of effects by macrosector (I)

**Table:** Diff-in-diff **labour productivity** by macrosector

	Labour productivity			
	Manufacturing and Constructions		Services	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	0.062*** [0.022]		0.054 [0.033]	
Ind 4.0*year 2018		0.047* [0.025]		0.037 [0.032]
Ind 4.0*year 2014		0.039 [0.024]		0.002 [0.029]
year 2018	-0.002 [0.019]	0.044** [0.021]	-0.056** [0.029]	-0.024 [0.029]
year 2014	-0.01 [0.014]	0.001 [0.018]	-0.081*** [0.02]	-0.045** [0.022]
other controls	Yes	Yes	Yes	Yes
constant	9.962*** [0.099]	10.048*** [0.268]	9.647*** [0.126]	8.855*** [0.277]
Obs	4470	4470	2493	2493
R2	0.328	-0.601	0.442	0.243

Source: longitudinal sample RIL[Orbis]. Note: controls include managerial and corporate governance characteristics, workforce composition, firms' productive characteristics, sectors of activity, nuts 2 regions, industrial relations

## Results: Heterogeneity of effects by macrosector (II)

**Table:** Diff-in-diff **wage** by macrosector

	Average wages			
	Manufacturing and Constructions		Services	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	0.026** [0.013]		0.01 [0.023]	
Ind 4.0*year 2018		0.02 [0.013]		0.009 [0.022]
Ind 4.0*year 2014		-0.006 [0.013]		-0.011 [0.02]
year 2018	0.004 [0.012]	0.069*** [0.012]	-0.03 [0.019]	0.025 [0.019]
year 2014	0.007 [0.009]	0.048*** [0.011]	-0.047*** [0.013]	-0.006 [0.016]
other controls	Yes	Yes	Yes	Yes
constant	10.178*** [0.067]	10.206*** [0.139]	9.905*** [0.094]	9.641*** [0.176]
Obs	4592	4592	2648	2648
R2	0.397	0.149	0.505	0.277

Source: longitudinal sample RIL[Orbis. Note: controls include managerial and corporate governance characteristics, workforce composition, firms' productive characteristics, sectors of activity, nuts 2 regions, industrial relations

# Results: Heterogeneity of effects by macrosector (III)

**Table:** Diff-in-diff **sales** by macrosector

	Manufacturing and construction		Services	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	0.059*		0.007	
	[0.031]		[0.050]	
Ind 4.0*year 2018		0.056**		0.036
		[0.028]		[0.031]
Ind 4.0*year 2014		0.013		0.022
		[0.024]		[0.027]
2018.anno	-0.015	-0.018	-0.02	-0.056*
	[0.029]	[0.025]	[0.039]	[0.030]
2014.anno	-0.017	-0.014	-0.084***	-0.081***
	[0.017]	[0.019]	[0.024]	[0.022]
management ch	Yes	Yes	Yes	Yes
workforce ch	Yes	Yes	Yes	Yes
firms ch	Yes	Yes	Yes	Yes
constant	10.598***	11.307***	10.323***	10.695***
	[0.146]	[0.311]	[0.319]	[0.288]
Obs	4590	4590	2654	2654
R2	0.335	0.057	0.498	0.255

Source: longitudinal sample RIL-Orbis. Note: Managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects.

# Heterogeneity of effects by firm age (I)

**Table:** Diff-in-diff **labour productivity** by firm age

	Labour productivity			
	Firm age <15		Firm age ≥ 15	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	-0.119 [0.078]		0.071*** [0.019]	
Ind 4.0*year 2018		-0.085 [0.078]		0.060*** [0.02]
Ind 4.0*year 2014		0.001 [0.072]		0.032 [0.02]
year 2018	0.105* [0.062]	0.053 [0.061]	-0.034** [0.017]	0.012 [0.017]
year 2014	0.008 [0.045]	-0.011 [0.054]	-0.037*** [0.012]	-0.023 [0.015]
other controls	Yes	Yes	Yes	Yes
constant	9.356*** [0.38]	9.516*** [0.396]	9.886*** [0.091]	9.797*** [0.197]
Obs	426	424	6545	6539
R2	0.468	0.332	0.376	

Source: longitudinal sample RIL[Orbis. Note: controls include managerial and corporate governance characteristics, workforce composition, firms' productive characteristics, sectors of activity, nuts 2 regions, industrial relations



## Heterogeneity of effects by firm age (II)

**Table:** Diff-in-diff **wage** by firm age

2[2]*	Average wages			
	2[2]*firms age 2018 <15		firms age 2018 ≥ 15	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	-0.067 [0.062]		0.025** [0.012]	
Ind 4.0*year 2018		-0.062 [0.062]		0.026** [0.012]
Ind 4.0*year 2014		-0.073 [0.058]		-0.001 [0.011]
year 2018	0.098* [0.052]	0.114** [0.048]	-0.018* [0.011]	0.047*** [0.01]
year 2014	0.015 [0.045]	0.054 [0.043]	-0.013* [0.007]	0.024*** [0.008]
other controls	Yes	Yes	Yes	Yes
constant	9.699*** [0.355]	9.539*** [0.35]	10.076*** [0.065]	10.042*** [0.112]
Obs	450	448	6798	6792
R2	0.371	-0.299	0.464	-0.367

Source: longitudinal sample RIL [Orbis. Note: controls include managerial and corporate governance characteristics, workforce composition, firms' productive characteristics, sectors of activity, nuts 2 regions, industrial relations

# Heterogeneity of effects by firm age (III)

**Table: Diff-in-diff sales by firm age**

	firms age 2018 <15		firms age 2018 >14	
	OLS	DIFF-FE	OLS	DIFF-FE
Ind 4.0	-0.203 [0.134]		0.063** [0.027]	
Ind 4.0*year 2018		0.013 [0.114]		0.053*** [0.020]
Ind 4.0*year 2014		-0.04 [0.110]		0.019 [0.018]
2018	0.210* [0.111]	0.015 [0.086]	-0.044* [0.023]	-0.037** [0.016]
2014	-0.011 [0.067]	0.002 [0.080]	-0.047*** [0.014]	-0.047*** [0.014]
Management ch	Yes	Yes	Yes	Yes
Workforce ch	Yes	Yes	Yes	Yes
Firms ch	Yes	Yes	Yes	Yes
Constant	9.849*** [0.627]	10.343*** [0.522]	10.545*** [0.127]	11.166*** [0.179]
Obs	451	449	6801	6795
R2	0.46	-0.307	0.426	-0.494

Source: longitudinal sample RIL-Orbis. Note: Managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects.

# Heterogeneity of effects along distributions (IV)

**Table:** Diff-in-diff quantile fixed effect estimates. **Labour Productivity**

Diff-in-diff quantile fixed effect estimates. Labour Productivity.			
	q10	q50	q90
Ind 4.0	-0.009 [0.019]	0.003 [0.013]	-0.014 [0.023]
Ind 4.0*year 2018	0.047* [0.026]	0.038** [0.018]	0.061* [0.032]
Ind 4.0*year 2014	0.038 [0.026]	0.015 [0.018]	0.038 [0.031]
Year 2018	0.026 [0.019]	0.021 [0.013]	0.016 [0.023]
Year 2014	0.010 [0.018]	-0.005 [0.013]	-0.046** [0.022]
Management characteristics	Yes	Yes	Yes
Workforce characteristics	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes
Constant	9.616*** [0.058]	9.904*** [0.04]	10.255*** [0.07]
Obs	6963	6963	6963

Note: Managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects. Clustered standard errors in parentheses: \* statistical significance at 10%, \*\* at 5%, \*\*\* at 1%. Source: our elaborations on RIL-Orbis merged sample

# Heterogeneity of effects along distributions (V)

**Table:** Diff-in-diff quantile fixed effect estimates. **Average Wage**

Diff-in-diff quantile fixed effect estimates. Average wage.			
	q10	q50	q90
Ind 4.0	0.002 [0.012]	-0.010 [0.006]	-0.014 [0.013]
Ind 4.0*year 2018	0.007 [0.017]	0.028*** [0.008]	0.054*** [0.018]
Ind 4.0*year 2014	0.004 [0.017]	0.003 [0.008]	-0.001 [0.017]
Year 2018	0.079*** [0.012]	0.049*** [0.006]	0.031** [0.013]
Year 2014	0.035*** [0.012]	0.024*** [0.006]	0.018 [0.012]
Management characteristics	Yes	Yes	Yes
Workforce characteristics	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes
Constant	9.830*** [0.037]	9.973*** [0.018]	10.109*** [0.039]
Obs	7240	7240	7240

Note: Managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects. Clustered standard errors in parentheses: \* statistical significance at 10%, \*\* at 5%, \*\*\* at 1%. Source: our elaborations on RIL-Orbis merged sample.

# Robustness checks

**Table A3.** Diff-in-Diff Fe estimates on common support PS.

	Labour productivity	Average wages	Sales per employee
Ind 4.0*year 2018	0.052*	0.013	0.017
	[0.03	[0.014	[0.031
Ind 4.0*year 2014	0.027	-0.014	-0.026
	[0.031	[0.014	[0.025
year 2018	-0.013	0.056***	-0.011
	[0.034	[0.013	[0.038
year 2014	-0.031	0.032**	-0.003
	[0.03	[0.013	[0.023
Management characteristics	YES	YES	YES
Workforce characteristics	YES	YES	YES
Firms' characteristics	YES	YES	YES
Constant	9.633***	10.026***	11.004***
	[0.276	[0.179	[0.357
N of Obs	5831	6058	6027
R2	0.118	0.224	0.158

Source: Longitudinal sample RIL-Orbis. Note: Managerial characteristics include level of education, age and gender of managers/entrepreneurs who run a firm, family ownership, occurrence of an external management; workforce characteristics controls for the composition by education, age, professional status, gender, contractual arrangements, citizenship; firms' characteristics include product innovation, process innovation, R&D, firms' age, foreign markets, foreign trade agreement, foreign direct investment, second level bargaining, membership to an employers' association. All regressions controls for 2-digit sectors of activity and nuts 2 regions fixed effects.

- ▶ Two- step procedure:
  - 1 - Propensity score matching (PSM) enabling to control for sample selection into the decision of I4.0 investment by adjusting for "observable" variables;
  - 2 - This "restricted" control group has been used to estimate the counterfactual effects of the I4.0 investment on our three outcomes through a Diff-in-Diff approach.

## Summarizing...

- ▶ The adoption of digital technologies exerts a positive effect on labour productivity, average sales and wages;
- ▶ The positive impact of I4.0 appears to be driven by **small and medium-size firms**: different time span of realization of productivity gains, in large companies the adoption of new technologies may require long adjustments of existing production processes;
- ▶ Sales increase more in medium-small and small companies with respect to the largest ones: I4.0 investments encompass a large set of technologies such as 3D printing or cybersecurity offering cost advantages without necessarily relying on economies of scale (Weller et al., 2015), hence enabling also SMEs to exploit such technologies for competitive purposes;
- ▶ Strong complementarities are required between digital technologies and organizational capabilities, managerial skills; RD and intangible investments, human capital and ICT-related skills: all these factors might require long time span to be fully in place enabling more **mature firms** to properly capture productivity gains from digital technologies (opposite effect in Acemoglu et al. 2022 - young firms).

## Summarizing...

- ▶ The economic size of the effect on productivity is approximately twice as large as the effect on average wages.  
→ This may be an indication of **poor redistribution** of gains from digital technology adoption, in line with the dominant pattern of wage-productivity decoupling detected in several countries over the last decade (OECD, 2018)
  - ▶ The adoption of I4.0 techs contribute to reshape productivity distribution by widening the gap between low-productive and high-productive companies;
    - (i) productivity gains detected at the top of the distribution are transferred to wages in high-paying firms defining a virtuous process going from digital transformation of companies to productivity and wages;
    - (ii) the redistributive effect of I4.0 techs does not occur among mid and low-productive/paying companies where a sizeable decoupling of wages from productivity arises.
- Unlike other economies (Schwellnus et al., 2018), in Italy the decoupling of wages from labor productivity seems to be related to laggard firms, whereas in (few) frontier-firms wages and productivity go almost hand in hand, according to our evidence, and are both positively associated to digitalization occurring at the workplace level.

## Similar results on US economy

- ▶ Similar results in Acemoglu et al. (2022) on US firm-level data (Census):
  1. US adopters have higher labor productivity and wages and lower labor shares;
  2. The use of these technologies is associated with a 15% increase in labor productivity, which accounts for 20–30% of the higher labor productivity achieved by the largest firms in an industry;
  3. Adopters report that these technologies raised skill requirements and led to greater demand for skilled labor, but brought limited or ambiguous effects to their employment levels;
  4. Reasonable to expect automation to increase employment in some firms while at the same time it reduces employment in others
  5. The use of advanced technologies involves a reassignment of labor from automated tasks to other complementary roles, including the maintenance, programming, and operation of specialized machinery.



## Further lines of research

- ▶ **Impacts of I4.0 investments on hiring rate, separation rate and training**
- ▶ Cirillo V., Mina A., Ricci A. (2022), Digital Technologies, Labor market flows and Training: Evidence from Italian employer-employees data, Roma, Inapp, WP 79

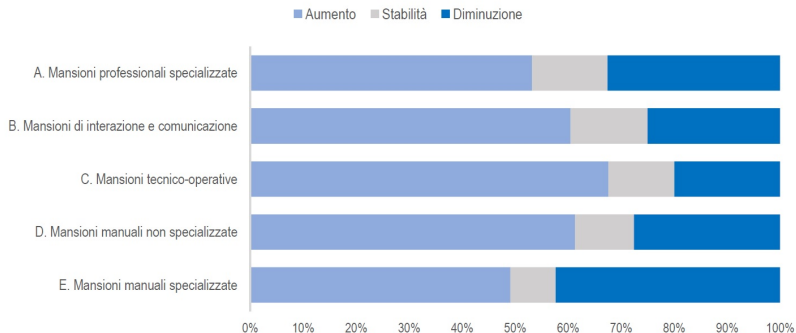
# Motivation

- ▶ New digital technologies promise dramatic improvements to production and service delivery processes, and imply deep changes in the nature and organisation of employment (Brynjolfsson and McAfee, 2014; Ford, 2015);
- ▶ Co-evolution of organisational capabilities and the external economic environment where firms operate significantly influences firm competitive advantage (Nelson and Winter, 1982; Dosi et al., 2000; Dosi and Marengo, 2015);
- ▶ The firm's ability to absorb new knowledge and new technologies; supply side and demand side factors drive adoption decisions (Hall and Khan, 2003), complementarities between tangible and intangible capital (Rosenberg, 1976);
- ▶ Neoclassical economists ("production function view") have stressed how firms can exploit the new technologies to change the relative use of production factors, their quality and the way these inputs are embedded in the organisation;
- ▶ Lack of suitable microdata has been limiting empirical research in this field (Raj and Seamans, 2019)

- ▶ Evidence on the effects of digital technologies on employment is less clear:
- ▶ Koch et al. (2021) that robot adoption produces from 20 to 25% output gains, reduces labour costs and positively contributes to firm employment growth (at an average rate of approximately 10%).
- ▶ Acemoglu et al. (2020) and Domini et al. (2021) study the effects of investments in robots made by French firms find positive employment growth effects.
- ▶ Genz et al. (2021) consider richer data on adoption, combined with administrative social security data, for German firms find evidence for improved employment stability, higher wage growth, and increased cumulative earnings in response to digital technology adoption.
- ▶ Bessen et al. (2019) exploit information on firms' expenditures on third-party automation, and their findings indicate that firm-level automation increases incumbent workers' probability to separate from their employer, followed by wage income losses that are only partly offset by social benefits.

## 14.0 and employment

FIGURA 10. IMPRESE CON ALMENO 10 ADDETTI IN BASE ALLA VARIAZIONE DELLA QUOTA DI OCCUPATI PREVISTA NEL TRIENNIO 2019-2021 IN CINQUE MANSIONI LAVORATIVE. Valori percentuali



- ▶ Companies that have invested in digital technologies in 2016-2018 or plan to invest in 2019-2021: expectations on employment change

# Data

Merge between 3 main sources of data:

1. **Comunicazioni Obbligatorie (COB-SISCO)**, an administrative archive provided by the Italian Ministry of Labor and Social Policies recording from 2009 each job relationship that started or ended (for firing, dismissal, retirement, or transformation of the contractual arrangement within the same firm) for all individuals working in Italy as an employee or through apprenticeship, temporary agency work arrangements, and parasubordinate collaborations;
2. **Archivio Statistico delle Imprese Attive (ASIA-Imprese)**, the archives of Italian firms provided by National Institute of Statistic (Istituto Nazionale di Statistica - ISTAT) containing information on Italian firms
3. **Rilevazione Imprese e Lavoro (RIL)** conducted by INAPP in 2010, 2015 and 2018 on a representative sample of partnerships and limited liability firms;

## Job flows

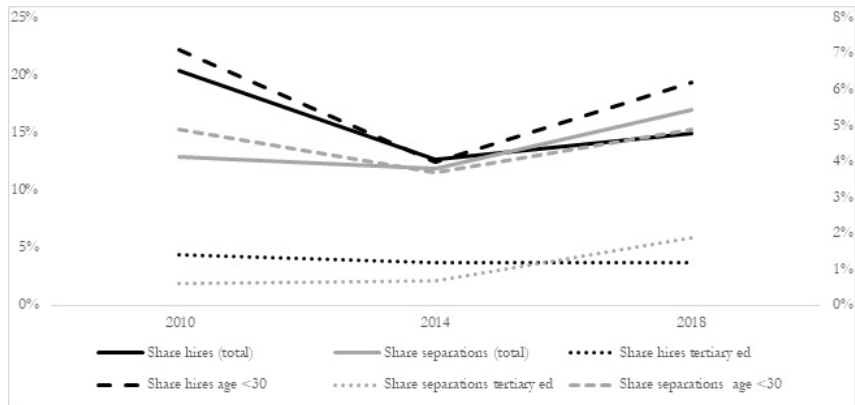
→ Linking the three different sources of information through firms' fiscal codes allows us to create a unique **longitudinal employer-employee linked database**:

→ information at the individual level stemming from COB-SISCO has been collapsed at the firm level for each year, high-quality information on the total number of hirings and separations for each firm by age group, educational titles and type of contract stemming from administrative archives.

→ having a clear picture not only of aggregate changes in employment, but also of the gross flows providing a much richer picture of the dynamics underlying net job creation figures (Criscuolo et al., 2014)

→ for example lower employment may be due to lower creation or higher destruction of jobs, which is crucial information when designing policies to tackle (eventual) employment effects of digital technologies.

# Hiring and separation rates over time by educational title and age



Source: our calculations on longitudinal component of RIL-COB-ASIA merged sample. Note: sampling weights applied.

\*share of employees hired/separated over total firm employment and by specific educational and age groups

## Share of firms investing in training, share of trained workers and average costs for training over time



Source: our calculations on longitudinal component of RIL-COB-ASIA merged sample. Note: sampling weights applied. Share of firms investing in training and share of trained workers on the left axis; training costs on the right axis.



# Empirical strategy

$$Y_{i,t} = \alpha + \beta_1 I_{4.0_i} + \beta_2 t + \gamma M_{i,t} + \delta W_{i,t} + \lambda F_{i,t} + \epsilon_{i,t}$$

$$Y_{i,t} = \alpha + \beta_1 I_{4.0_i} + \beta_2 t + \beta_3 I_{4.0_i} \times t + \gamma M_{i,t} + \delta W_{i,t} + \lambda F_{i,t} + \mu_i + \epsilon_{i,t}$$

$$T = [2010, 2014, 2018]$$

- ▶  $Y_{i,t}$  indicates alternatively share of new hired, the share of separated over firm total employment and workplace training proxied by adoption of training, share of trained employees, the (log of) training costs per employees;
- ▶  $I_{4.0_i}$  is a dummy equal to 1 whether the firm has invested in at least one technology among Internet of things (IoT), Robotics, Big data analytic, Augmented reality and Cybersecurity introduced over 2015-2017, 0 otherwise;
- ▶  $M_{i,t}$  includes managerial and corporate governance characteristics;
- ▶  $W_{i,t}$  represents the workforce composition;
- ▶  $F_{i,t}$  is a rich set of firms' productive characteristics, geographical location and sectoral specialization;
- ▶  $t$  is a time indicator;
- ▶  $\mu$  firm fixed-effects capturing time invariant unobserved heterogeneity;
- ▶  $\epsilon_{i,t}$  is the idiosyncratic error term (clustered standard error by firm);
- ▶ Pooled OLS and Fixed effects (FE);
- ▶ Heterogeneity by firm size, sector of activity and firm age.

**Table:** Diff-in-diff fixed effects estimates. **Hiring rate**

Diff-in-diff fixed effects estimates. Dep var: Hiring rate

	Workers over total employ- ment	Workers <30 y.o. over total employ- ment	Graduated workers
I4.0* year 2018	0.019** [0.008]	0.008* [0.005]	0.004 [0.002]
I4.0*year 2014	0.013* [0.008]	0.008 [0.005]	0.001 [0.003]
year 2018	-0.026*** [0.007]	-0.008* [0.004]	-0.002 [0.002]
year 2014	-0.045*** [0.006]	-0.016*** [0.004]	-0.003* [0.002]
Firms registering vacancies	0.028*** [0.006]	0.014*** [0.004]	0.001 [0.002]
Log wage per employee	-0.021*** [0.004]	-0.007*** [0.002]	-0.003*** [0.001]
Other controls	Yes	Yes	Yes
Constant	0.468*** [0.088]	0.157*** [0.061]	0.004 [0.044]
N of Obs	11257	11257	11257
R2	0.064	0.045	0.03

**Table:** Diff-in-diff fixed effects estimates. **Separation rate**

Diff-in-diff fixed effects estimates. Dep var: Separation rate

	Workers over total empl	Workers <30 y.o. over tot empl	Graduated workers over tot empl
14.0* year 2018	-0.016** [0.008]	0.000 [0.005]	0.002 [0.002]
14.0*year 2014	-0.011 [0.008]	-0.003 [0.004]	-0.002 [0.002]
year 2018	0.030*** [0.007]	0.000 [0.004]	0.005*** [0.002]
year 2014	-0.004 [0.006]	-0.007* [0.004]	0.002 [0.002]
Firms registering vacancies	0.021*** [0.006]	0.009*** [0.003]	0.001 [0.002]
Log wage per employee	0.019*** [0.004]	0.003 [0.002]	0.002 [0.002]
Other controls	Yes	Yes	Yes
Constant	-0.009 [0.083]	0.109** [0.045]	0.013 [0.02]
N of Obs	11257	11257	11257
R2	0.028	0.015	0.013

Source: our calculations on RIL-COB-ASIA merged sample. Other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.

**Table:** Diff-in-diff fixed effects estimates. **Workplace training**

Diff-in-diff fixed effects estimates. Dep var: Workplace training

	Training invest- ment	Share of trained employees	Training costs per employee
I4.0* year 2018	0.050*** [0.019]	0.035** [0.016]	0.303*** [0.108]
I4.0*year 2014	0.036* [0.02]	0.026 [0.017]	0.106 [0.11]
year 2018	0.158*** [0.014]	0.177*** [0.012]	0.761*** [0.076]
year 2014	0.096*** [0.014]	0.107*** [0.011]	0.549*** [0.072]
Firms registering vacancies	0.047*** [0.016]	0.029** [0.014]	0.329*** [0.093]
Log wage per employee	0.012 [0.009]	0.017* [0.009]	0.108* [0.06]
Other controls	Yes	Yes	Yes
Constant	0.175 [0.176]	-0.256 [0.162]	-2.205* [1.301]
N of Obs	11257	11251	10214
R2	0.061	0.087	0.062

Source: our calculations on RIL-COB-ASIA merged sample. Other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.

**Table:** Diff-in-diff fixed effects estimates. Hiring rate

Table 11. Diff-in-diff fixed effects estimates. Dep var: Hiring rate

	2[2]* Workers over total employ- ment	2[2]*Workers <30 years old over total employment	Graduated workers over total employ- ment
IoT* year 2018	0.005 [0.014]	0.009 [0.008]	0.008* [0.004]
IoT*year 2014	-0.003 [0.013]	0.003 [0.007]	0.005 [0.005]
year 2018	-0.020*** [0.006]	-0.005 [0.004]	-0.001 [0.002]
year 2014	-0.041*** [0.005]	-0.014*** [0.003]	-0.003** [0.001]
Firms registering vacancies	0.028*** [0.006]	0.014*** [0.004]	0.001 [0.002]
Log wage per employee	-0.021*** [0.004]	-0.007*** [0.002]	-0.003*** [0.001]
Other controls	Yes	Yes	Yes
Constant	0.469*** [0.088]	0.159*** [0.061]	0.006 [0.044]
N of Obs	11257	11257	11257
R2	0.064	0.044	0.031

Source: our calculations on RIL-COB-ASIA merged sample. Other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.

# Internet of Things

**Table:** Diff-in-diff fixed effects estimates. Dep var: Separation rate.

Table 12. Diff-in-diff fixed effects estimates. Dep var: Separation rate.

	2[2]* Workers over total employ- ment	2[2]*Workers <30 years old over total employment	Graduated workers over total employ- ment
IoT* year 2018	-0.003 [0.013]	0.007 [0.007]	0.012** [0.005]
IoT*year 2014	-0.006 [0.013]	-0.001 [0.006]	0.008* [0.005]
year 2018	0.024*** [0.006]	0.000 [0.003]	0.004*** [0.001]
year 2014	-0.008 [0.005]	-0.008*** [0.003]	0.001 [0.001]
Firms registering vacancies	0.021*** [0.006]	0.009*** [0.003]	0.000 [0.002]
Log wage per employee	0.019*** [0.004]	0.003 [0.002]	0.002 [0.002]
Other controls	Yes	Yes	Yes
Constant	-0.012 [0.083]	0.108** [0.045]	0.014 [0.02]
N of Obs	11257	11257	11257
R2	0.028	0.015	0.014

Source: our calculations on RIL-COB-ASIA merged sample. Other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.

**Table:** Diff-in-diff fixed effects estimates. Dep var: Hiring rate.

	2[2]* Workers over total employ- ment	2[2]*Workers <30 years old over total employment	Graduated workers over total employ- ment
Robot* year 2018	0.024** [0.012]	0.009 [0.007]	0.004* [0.002]
Robot *year 2014	0.026*** [0.010]	0.014** [0.006]	0.003 [0.002]
year 2018	-0.021*** [0.006]	-0.005 [0.004]	-0.001 [0.002]
year 2014	-0.043*** [0.005]	-0.014*** [0.003]	-0.003* [0.001]
Firms registering vacancies	0.028*** [0.006]	0.014*** [0.004]	0.001 [0.002]
Log wage per employee	-0.021*** [0.004]	-0.007*** [0.002]	-0.003*** [0.001]
Other controls	Yes	Yes	Yes
Constant	0.469*** [0.088]	0.158*** [0.061]	0.006 [0.044]
N of Obs	11257	11257	11257
R2	0.064	0.044	0.031

Source: our calculations on RIL-COB-ASIA merged sample. Other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.

**Table:** Diff-in-diff fixed effects estimates. Dep var: Separation rate.

	Workers over total employ- ment	Workers <30 years old over total em- ployment	Graduated workers over total employ- ment
Robot* year 2018	-0.011 [0.011]	0.002 [0.007]	-0.001 [0.002]
Robot*year 2014	-0.012 [0.009]	0.004 [0.005]	0.001 [0.002]
year 2018	0.025*** [0.006]	0.000 [0.003]	0.006*** [0.001]
year 2014	-0.007 [0.005]	-0.009*** [0.003]	0.001 [0.001]
Firms registering vacancies	0.021*** [0.006]	0.009*** [0.003]	0.001 [0.002]
Log wage per employee	0.019*** [0.004]	0.003 [0.002]	0.002 [0.002]
Other controls	Yes	Yes	Yes
Constant	-0.011 [0.083]	0.108** [0.045]	0.013 [0.02]
N of Obs	11257	11257	11257
R2	0.028	0.015	0.012

Source: our calculations on RIL-COB-ASIA merged sample. Other controls include: managerial characteristics (education, age and gender), family ownership and the presence of external managers; workforce composition (education, professions, age, female, contractual arrangements); firms productive characteristics such as NACE e sectors, NUTS 2 regions, international markets, second level bargaining, multinationals, vacancy. Clustered robust standard errors in parentheses.



## Exploring tech heterogeneities...

- ▶ Compared to general results, we detect that:
  - cybersecurity, IoT and robotics are associated with higher hiring rate for graduates,
  - whereas no significant effects emerge for separations, except for cybersecurity which is negatively associated to firm level separation rate;
- ▶ **Our evidence discards, so far, a labour-displacing effects of I4.0 technologies on jobs, conversely, they appear to be associated to job creation at least for young workers;**
- ▶ Further research is needed to explore which kind of workers are more likely to be affected by the digital transformation of companies since workers can be unevenly involved in these processes considering peculiarity of tasks they perform and ability to intervene in the digital transformation.
- ▶ This is in line with the vision in Zysman and Kenney (2018) → processes can never be totally 'automated' and remains a domain of human creativity and initiative (Fareri and Solinas, 2021).
- ▶ **What about "low-value added activities"?**
  - On-going qualitative research on automation in logistic and cleaning activities...

# Industry 4.0 and work organization

- ▶ The relationship between I4.0 investments and work organization: a qualitative research approach
  1. The Fondazione Sabattini research project - closed (published book by "Il Mulino");
  2. Case studies of Automation in Services funded by JRC-European Commission Seville, realized in collaboration with SSSA and UNIMORE

# The Fondazione Sabattini research project

Research project coordinated by Claudio Sabattini Foundation,  
commissioned by FIOM-CGIL (Bologna)

Garibaldi and Rinaldini (2022) Il lavoro operaio digitalizzato. Inchiesta nell'industria metalmeccanica bolognese. Il Mulino.

- ▶ Interviews within the establishments in areas made available by the company or by the union delegates;
- ▶ Focus groups with firm-level union delegates;
- ▶ *Visits* to the different areas and departments of the production plants;
- ▶ Interviews with the management of the companies and other technical figures;
- ▶ Collection of business documents and other publications;
- ▶ MEGA project (repository for storage/material exchange between researchers) → <https://mega.nz>



Main research question: Consequences of Industry 4.0 on work and labour

# Field Research: one year of semi-structured interviews

## Piemonte:

COMAU - Grugliasco (TO);  
Fiat Power Train - Torino

## Veneto:

CAREL - Brugine (PD);  
COSTAN - Belluno;  
MIDAC - Soave Veronese (VR);  
Fonderie Zanardi - Minerbe (VR)

## Lombardia:

ABB - Dalmine (BG);  
Alstom - Sesto San Giovanni (MI);  
ST Microelectronics (STM) - Agrate and  
Castelletto (MI);  
Magneti Marelli - Corbetta (MI);  
General Electric - Talamona (SO);  
Kosme - Roverbella (MN)

## Emilia Romagna:

1- Ducati Motor - Bologna;  
2- IMA - Ozzano (BO);  
3- Lamborghini Manufacturing -  
Sant'Agata Bolognese (BO);  
4- Bonfiglioli Group - Lippo di  
Calderara Di Reno (BO);  
5- Toyota Motor Handling  
Manufacturing - former known as  
6- CESAB - Bologna;  
7- Marchesini - Pianoro (BO);  
Cefla - Imola (Bo);  
SACMI - Imola (BO);  
Comer - Reggiolo (RE);  
Carpenfer - Reggiolo (RE);  
Interpump - Calerno - Sant'Illario  
d'Enza (RE);  
Graniti Pandre - Casalgrande (RE)

## Puglia:

Bosch - Modugno (BA)



# Field Research: a sample of Italian manufacturing firms

- ▶ Case studies articulated by industrial sectors
  1. Machinery and equipment for industry and trade:  
IMA, Cesab-Toyota, Cefla, Costan, Sacmi, Kosme;
  2. Parts and electromechanical components:  
Carel, Bonfiglioli, Midac, ABB Bergamo, Magneti Marelli Milan, STM Milan;
  3. Consumer Products:  
Ducati, Lamborghini;
- ▶ Research carried out interviewing both the management and the workers of the companies
- ▶ Methodology based on semi-structured interviews (about 45 minutes face-to-face anonymous interviews)

# The JRC-UNIBA-SSSA-UNIMORE research project

- ▶ Examining the socio-economic impact of automation in the service industries;
- ▶ Supporting the research activity undertaken by the Employment team in JRC Unit B4, in collaboration with DG Employment.
- ▶ Carrying out three case studies, one for each technology (AGVs, Healthcare monitoring devices, cleaning robots), to examine:
  1. their impact on business model, production and economic process in the service industries;
  2. the implications of these changes for work organization, occupational health and safety, and job quality;
  3. the implications of these changes in terms of tasks, occupations and skill requirements;
  4. the drivers and barriers for the automation of services in the EU and potential future developments.

Thank you

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