For whom the bell tolls: the firm-level effects of automation on wage and gender inequality

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Wage inequality between and within firms

- **Wage inequality between firms** (mean wage):
  $\rightarrow$ sector, size, productivity, technology, employment structure

- **Wage inequality within firms** (90/10 ratio, wage dispersion)
  $\rightarrow$ role of employee characteristics (occupation, tenure, employment structure, gender...)

Automation and the future of work

Labor market effects of AI/automation

Theoretical mechanisms

(cf. Acemoglu and Restrepo, 2019 NBER chapter; Abowd et al., 1999 - AKM)

- Displacement effect (Automation replaces human tasks)
  - labor share and overall wages $\downarrow$
  - change in relative labor demand $\rightarrow$ some workers are more demanded - and wage inequality $\uparrow$
- Productivity and scale effects (Automation makes labor and capital more productive)
  - wages $\uparrow$ (**rent sharing**)
  - Heterogeneous productivity effects $\rightarrow$ wage inequality $\uparrow$
  - Automation requires the creation of new (human) tasks
- Employee matching effect (Change in the profile of new hires)
  - **Sorting**: High wage workers attracted to better firms (AKM)
  - Wage differences across new hires and incumbent workers

Labor market effects of AI/automation - Empirical evidence

Effects on employment

- *Aggregate studies* fail to find a consensus (Acemoglu et al., 2020; Acemoglu and Restrepo, 2017; Dauth et al., 2018; Graetz and Michaels, 2018; Klenert et al., 2020)
- *Firm-level studies* consistently show increase in employment of adopters of automation/robots (Acemoglu et al., 2020; Aghion et al., 2020; Bessen et al., 2020; Bonfiglioli et al., 2020; Domini et al., 2021; Koch et al., 2019)

Effect on wage (inequality) less investigated

- *Employee level*: After an automation cost spike, incumbent workers experience wage income loss (esp. small firms) (Bessen et al., 2019, NL)
- *Firm level*: Robots increase wages for high-skilled/tech workers wrt. production workers and thus within-firm inequality (Barth et al., 2020 Norw.; Humlum, 2020, DK)

Labor market effects of AI/automation - Empirical evidence

Effects on gender wage gap

- *Why?* Gender differences in occupations may drive differences in exposure to automation (Brussevich et al., 2019)
- *Country level*: 10% investments in robots is associated to a 1.8% increment in the gender wage gap. (Aksoy et al., 2020)
- *Commuting zones*: investments in robots decreases the wage gap; computer adoption increases it (Ge and Zhou, 2020, US)
- *Firm level*: automation increases more the wage of males than female workers (Pavlenkova et al., 2021, EST)

The paper in brief

How much of wage inequality is due to differences within firms rather than between firms?

What is the effect of automation/AI investments on wage and wage inequality within firms?

What are the mechanisms?

The paper in brief

- We study the impact of investment in automation and AI on within-firm wage inequality in adopting firms in France, 2002-2017
- We measure firm-level adoption of such technologies by resorting to imports of automation/AI related goods
- A careful inspection of the data suggest that most of wage inequality is due to differences among workers belonging to the same firm, rather than by differences between sectors, firms, and occupations
- Employing an event study, we show that automation/AI spikes are not followed by increase in within-firm or gender wage inequality
- On the contrary, wages at adopting firms tend to increase evenly at different percentiles of the distribution

Data and variables

Data and variables

Datasets

- DADS *Postes*: employer-employee database (social security forms) covering all French firms *with employees*
  - worker-level information on gross yearly remuneration; hours worked; age; gender; occupation
  - we exclude primary sector (NACE 01-09), household employers, and public administration
  - Firm perspective (not worker's)
- DGDDI data: customs database
  - transaction-level information on value, product sector, etc.

Main variables:

- Within-firm measures of (hourly) wage inequality: p90/p10 and SD (based on worker-level wage = yearly remuneration / hours)
- Firm-level events (spikes) of investment in automation and/or AI (based on imports of relevant technologies)

Identifying and characterising automation and AI events

We use **imports** of capital goods **embedding automation/AI** technologies

- ***Why?*** Lack of systematic firm-level info on adoption of automation/AI technologies
  - Done by several studies (Acemoglu et al., 2020; Aghion et al., 2020; Bonfiglioli et al., 2020; Dixon et al., 2019; Domini et al., 2021)
  - Exceptions: survey data (Bessen et al., 2019; Dinlersoz et al., 2018)
  - We are aware of and discuss limitations
- ***How?*** Identified via product codes ▸ appendix
  - We build on a taxonomy by Acemoglu and Restrepo (2018)
- ***Characterisation*** Spiky behaviour typical of investment (cf. Domini et al. 2020): rare *across* firms and *within* firms
  $\rightarrow$ **Largest event** for each firm = automation/AI **spike**
- ***Selection effects*** Firms adopting automation/AI are different from those who don't
  - Larger, more productive, paying higher wages ▸ appendix
  - More unequal (90/10 ratio, wage sd, gender inequality) ▸ appendix

Automation/AI-related goods as investment in tangible asset

Imports of such goods display the typical *spiky behavior* of investment in tangible assets
(Asphjell et al., 2014; Domini et al., 2021; Grazzi et al., 2016):

- They are *rare across firms*
  - Among all importers, in a given year, only around 14% of firms import automation- or AI-related products
  - and less than half of them do it at least once over 2002-2017
- They are *rare within firms*
  - Among firms that import such goods at least once, close to 30% do it only once
  - and the frequency decreases smoothly with higher values
- A firm's largest episode of import of such goods (in a year) accounts for a very large share (around 70%) of its total across years

Automation/AI investment spike = largest event for each adopting firm

Decomposing wage inequality

Decomposing wage inequality (I)

We decompose wage inequality among all workers (in a given year, 2017) at different levels of disaggregation

- Within: wage inequality due to differences within sectors, occupations, or sector-occupation groups
- Between: wage inequality due to differences across sectors, occupations, and sector-occupation groups (mirror image, not shown)

	(%) Within sector	(%) Within occupation	(%) Within sector-occupation
All firms	78	55	46
Adopters of AI/automation	80	52	45

Sector is 2-digit NAF of the firm; occupation (broadly) is 1-digit CS of the worker (managers and white-collars; supervisors and technicians; clerks; skilled production workers; unskilled skilled production workers; residual workers).

Decomposing wage inequality (II)

- Within vs. between firms (in same sector)
- Within vs. between firms (in same sector-occupation)

	(%) Within firms, sector level	(%) Within firms, sector-occupation level
All firms	67	58
Sample 3 (+ adopters)	76	70

Numbers are computed for each sector/sector-occupation separately and then aggregated by taking an employment-weighted average.

→ *Most of wage differences in sectors(-occupations) are due to within-firm differences*

Regression analysis

Effect of investment in automation/AI on wage

Spiky behaviour
⇒ event study (Bessen et al., 2020)

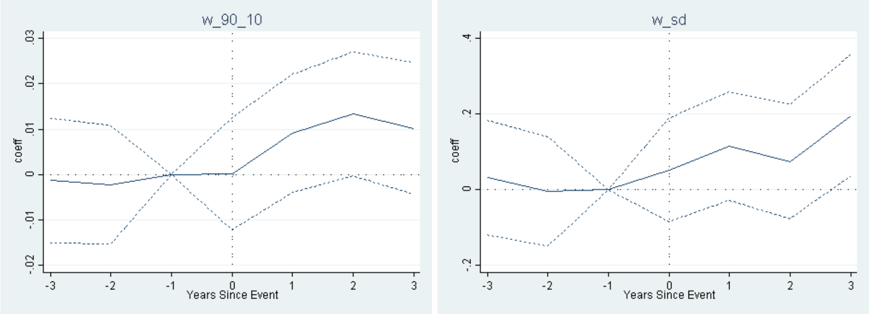
Selection into automation/AI
⇒ within adopters of AI/automation (i.e. firms importing at least once automation/AI with ≥ 10 emp)
⇒ exploits heterogeneity in timing of the event among relatively similar firms

$$y_{ijt} = \sum_{k \neq -1; k_{min}}^{k_{max}} \beta_k D_{kit} + \delta_i + \zeta_{jt} + \varepsilon_{it} \tag{1}$$

y_{ijt} is the dependent variable of interest for firm i at time t in sector j; D_{kit} is a dummy = 1 if index= k for firm i in year t

Centered at $t-1$, so the coefficient on $t=0$ measures what happens in the year of the spike, with respect to the previous year

Wage inequality (p90/p10 and SD)

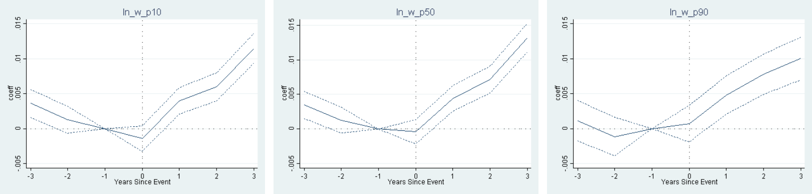


Solid line: coefficients β_{-3} to β_3. Blue lines: conf. intervals at 5%

- Slight increase but most coefficients β_k are not significant

Wage increase at percentiles

- *Are automation/AI and wage disconnected?*
- *Is the wage change evenly distributed within adopting firms?*

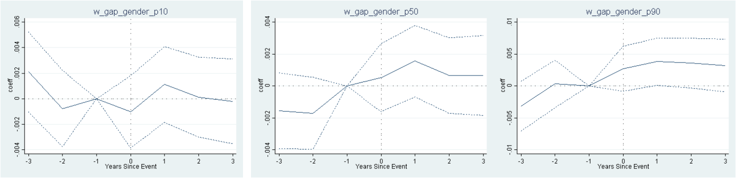


Solid line: coefficients β_{-3} to β_3. Blue lines: conf. intervals at 5% ; Wage is in log so coefficients are read as percentage change

- 3 years after the spike, mean wage increases of around 1%

Gender wage gap

- Ratio between a certain percentile of women's wage distribution and the same percentile for men
- Higher ratio = less gender inequality

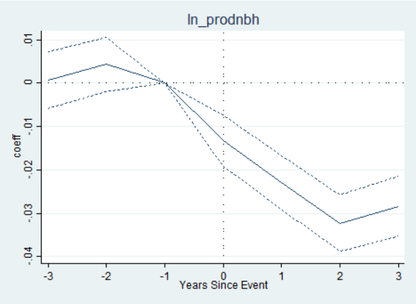


Solid line: coefficients β_{-3} to β_3. Blue lines: conf. intervals at 5% .

- Gender gap is almost unchanged after the spike
- Small and barely significant increase is detectable at the 90th percentile (where gap was higher)

Mechanism: productivity channel

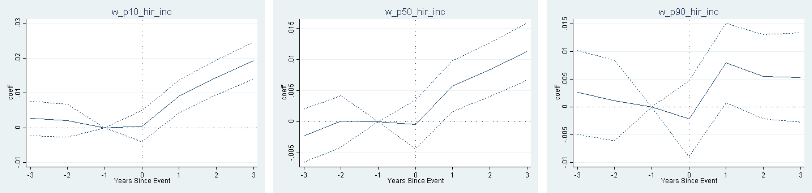
- *Is the wage increase due to a productivity pass-through / rent sharing process?*



- 3% Negative shock to productivity after two years, then stabilizes
- Aligned with investment spike literature (Power, 1998)
- Role of institutional context in downward wage rigidity

Mechanism: employee matching channel (AKM)

- *Is the profile of new hired workers changing in relation to the adoption of automation/AI?*



- After 3 years, at the 10th percentile, firms tend to pay an hourly wage to new workers that is around 1% higher w.r.t. one year before the spike
- Similar trend at the 50th, no significant effect at the 90th percentile
- **Explanation?**: matching + wage rigidity among incumbents

Robustness checks

Changing the **definition** of spikes

- AI versus automation only spikes
- More restrictive spike definition

Changing the **sample** of analysis

- Manufacturing vs. Services
- Excluding potential re-sellers of automation/AI products

No major differences in our results and interpretations

Summing up

- Within-firm wage inequality is pervasive also in France
- We look at the impact of AI/automation on such measure:
  - Automation/AI spikes are not followed by an increase in wage inequality
  - Limited increase (1%) in wage even across the employment distribution
  - This is not due to rent-sharing (negative effect on productivity)
  - This is at least partly associated with newly hired workers (aligned with the AKM framework)
- **Role of technology?** Different from what has been found in the case of robot adoption (Barth et al., 2020; Humlum, 2020)
- **Role of labour institutions?** High wage rigidities

Data appendix

Product codes (HS6) embedding relevant technologies

Label	HS-2012 codes
1. Industrial robots	847950
2. Dedicated machinery	847989
3. Automatic machine tools (incl. Numerically controlled machines)	845600-846699, 846820-846899, 851511-851519
4. Automatic welding machines	851521, 851531, 851580, 851590
5. Weaving and knitting machines	844600-844699, 844700-844799
6. Other textile dedicated machinery	844400-844590
7. Automatic conveyors	842831-842839
8. Automatic regulating instruments	903200-903299
9. 3-D printers	847780
10. Automatic data processing machines	847141-847150, 847321, 847330
11. Electronic calculating machines	847010-847029

Codes for (1)-(8) based on Acemoglu and Restrepo (2018, A-12-A14), for (9) on Abeliansky et al., 2015, p. 13, for (10)-(11) on ALP matching of USPC code 706 ('Data processing - Artificial Intelligence') to HS codes (Lybbert and Zolas, 2014) and own expertise.

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Sample construction

Cleaning: remove *annexes* jobs (below duration, working-time, and salary thresholds) and apprentice workers ($\approx$ 3.5%)

Various samples defined

1. restrict to importing firms
2. restrict to firms with $\geq$10 employees
3. restrict to firms importing automation/AI (at least once)

	Firm-year obs	Nb. firms	Share in nb. of firms	Share in employment
All firms	20,231,242	3,204,497	100%	100% ($\approx$16 M)
Sample 1	2,726,445	291,139	9.08	54.50
Sample 2	1,140,139	96,128	3.02	51.79
Sample 3	506,893	40,087	1.25	37.24

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Comparing firms with and without an automation/AI spike

	No automation/AI	Automation/AI	T-test
Number of observations	633,246	506,893	
Number of firms	56,041	40,087	
Number of employees	55.38	177.09	***
Wage per hour (mean)	18.19	20.49	***
Wage standard deviation	8.68	10.73	***
90-10 wage ratio	2.38	2.53	***
Female-to-male wage ratio	0.881	0.840	***
Wage per hour (p1)	10.31	10.45	***
Wage per hour (p10)	11.77	12.60	***
Wage per hour (p50)	15.68	17.49	***
Wage per hour (p90)	28.18	32.11	***
Wage per hour (p99)	46.82	58.86	***
Female-to-male wage ratio (p1)	1.07	1.06	***
Female-to-male wage ratio (p10)	1.01	0.98	***
Female-to-male wage ratio (p50)	0.94	0.91	***
Female-to-male wage ratio (p90)	0.83	0.79	***
Female-to-male wage ratio (p99)	0.73	0.65	***

Based on sample 2 (importing firms with at least 10 employees), 2002-2017.

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