For whom the bell tolls: the effects of automation on wage and gender inequality within firms

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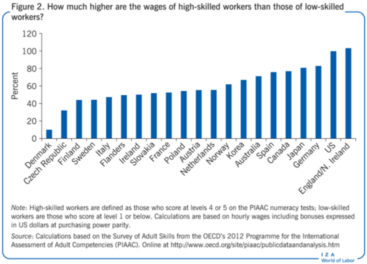
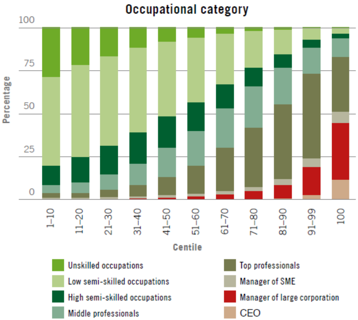
Explaining wage inequality

What we know: occupational differences and the skill wage premium





Sources: Left figure is Broecke (2016), right figure from from ILO (2016).

→ Note the heterogeneity of wages within occupations!

What we know: sectoral differences and structural change

Figure 46 Occupational categories and wage differentials: Establishments classified by economic sector, ranked in columns by average hourly wage at enterprise level

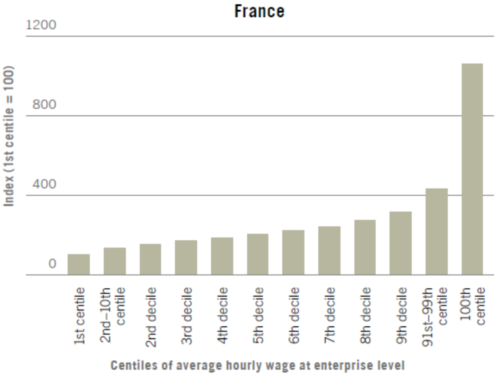
Note: H&R = hotels and restaurants; TR = wholesale and retail trade; SS = social services; MF = manufacturing; C&U = construction and utilities; OS = other service providers; M&Q = mining and quarrying; TC = transport and communications; R&F = real estate and financial activities. The classification by occupation follows ISCO-88: CEO = chief executive officer; MCRP = manager of a corporation; MSME = manager of an SME; HPF = high professional occupation; MPF = mid-level professional occupation; HSKO = higher semi-skilled occupations; LSKO = lower semi-skilled occupations; LSO = low or unskilled occupations. In (b), “lower occupational skills” includes the low or unskilled occupations and those working in the lowest semi-skilled occupations; “higher occupational skills” includes those working as CEOs, as managers of corporations or SMEs, or in top professional occupations.

Source: ILO estimates based on SES database.

Source: ILO (2016)

The role of firms in aggregate wage inequality

How to explain differences within occupations and sectors?
→ firm characteristics



Source: ILO (2016)

Wage inequality between and within firms

(cf. Song et al. 2019)

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

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

Labor market effects of AI/automation

Two conflicting theoretical effects at play
(cf. Acemoglu and Restrepo, 2019 NBER chapter)

- 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 $\uparrow$

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  - 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)
  - change in firm performance (sales, profits, size)
  - overall capital, employment and wages $\uparrow$ (rent sharing + sorting effect)
  - change in relative labor demand (SBTC $\rightarrow$ some workers become more productive) and wage inequality $\uparrow$
  - Automation requires the creation of new (human) tasks

Labor market effects of AI/automation - Empirical evidence

Effects on employment

- *Aggregate studies* fail to find a consensus
  (Acemoglu and Restrepo, 2017; Acemoglu et al., 2020; 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., 2020; Koch et al., 2019)

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Effect on wage (inequality) less investigated

- *Employee level* Bessen et al., (2019), using a Dutch survey after an automation spike, incumbent workers are more likely to separate and experience wage loss
- *Firm level* Barth et al., (2020), using Norwegian administrative data: robots increase wages for high-skilled workers and thus within-firm inequality

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?

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

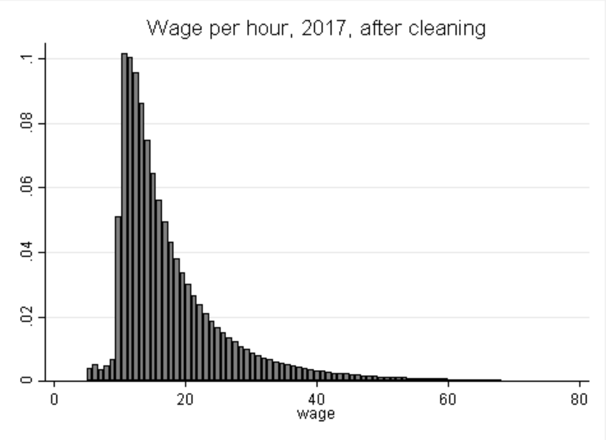
Datasets

- 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)

Wage distribution of workers



All firms; minimum wage that year around 10 euros.

Identifying and characterising automation

Why using imports of capital goods embedding automated/AI technologies

- ***Why?*** *Firms change their production process via investment*
  $\rightarrow$ Intermediate goods that embed automation technologies

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  $\rightarrow$ Product information from customs data (see next slide)
  (Acemoglu and Restrepo, 2018)

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- ***Why?*** *Firms change their production process via investment*
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- ***What?*** *Identified via product codes*
  $\rightarrow$ Product information from customs data (see next slide) (Acemoglu and Restrepo, 2018)

- ***How?*** *How often do they buy such goods?*
  $\rightarrow$ spiky behaviour typical of investment (cf. Domini et al. 2020):
  - *rare across firms*
  - *rare within firms*

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.

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., 2020; 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

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.

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

Decomposing wage inequality

Decomposing wage inequality (I)

We decompose wage inequality among all workers (in a given year, 2017) in *within* and *between* components at different levels of disaggregation:

	(%) Within sector	(%) Within occupation	(%) Within sector-occupation
All firms	78	55	46
Sample 1 (importing firms)	80	53	46
Sample 2 (+ above 10 emp)	80	52	45
Sample 3 (+ adopters)	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).

Notice that the between component (wage inequality due to differences across sectors, occupations, and sector-occupation groups), though not shown, is the mirror image of the values reported in the table.

Decomposing wage inequality (II)

We further calculate the share of wage inequality that, inside each sector or inside each sector-occupation, is due to the within-firm component

	(%) Within firms, sector level	(%) Within firms, sector-occupation level
All firms	67	58
Sample 1 (importing firms)	75	68
Sample 2 (+ above 10 emp)	76	70
Sample 3 (+ adopters)	76	70

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

Notice that the between component (wage inequality due to differences across firms), though not shown, is the mirror image of the values reported in the table.

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

Regression analysis

Effect of investment in automation/AI on wage inequality

Spiky behaviour of imports of automation- and AI-related goods
$\Rightarrow$ event study (Bessen et al., 2020)

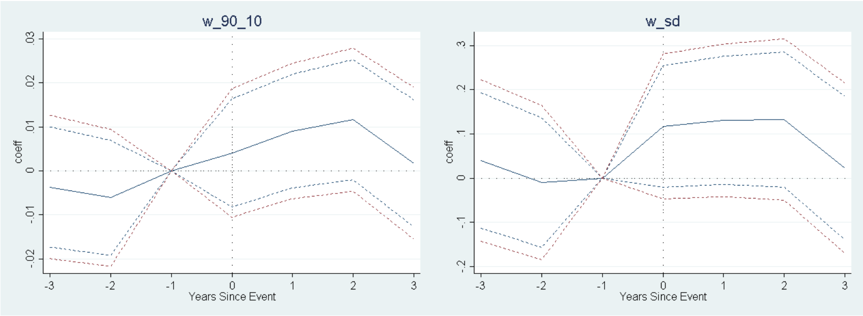
Sample 3: firms importing at least once automation/AI with ≥ 10 emp.
$\Rightarrow$ exploit heterogeneity in timing of the event among relatively similar firms

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

y_{ijt} is the dependent variable of interest for firm i at time t in sector j; dummies D_{it+k} are leads and lags w.r.t. to the spike year (k=0); X_{it} is a set of controls including avg age of the workforce and share of female workers

Centered at -1, so the coefficient on 0 measure 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 / red dotted lines: conf. intervals at 5% and 10%.

Coefficients β_k are not significant employing either measure of inequality
Same for manufacturing and services separately

Gender wage gap

Ratio between a certain percentile of women's wage distribution and the same percentile for men

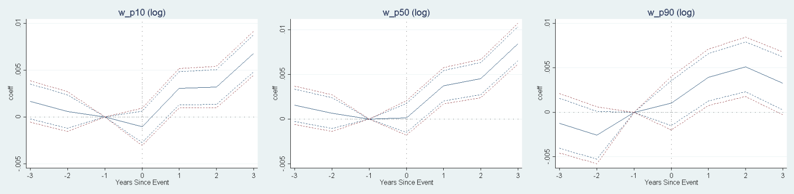
Solid line: coefficients β_{-3} to β_3. Blue / red dotted lines: conf. intervals at 5% and 10%.

Gender gap is almost unchanged after the spike; a small and barely significant increase is detectable at the 90th percentile

Wage increase at percentiles

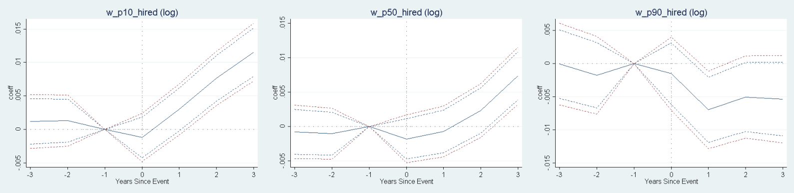
Within-firm (gender) wage inequality not affected by spike
What's going on?

- Are automation and wage disconnected?
- Is the wage change evenly distributed?



Wage is in log $\Rightarrow$ coefficients as percentage change
3 years after the spike, mean wage increases of around 0.6%
N.B. No evidence of pre-spike trend

Newly hired workers



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

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% or lower) in wage even across the employment distribution
  - This is at least partly associated with newly hired workers, especially at the lower end of the wage distribution
    - This could suggest new hires are purported at acquiring skills and competencies required by new tech
    - Data limitations inhibit the possibility to test for this
  - Magnitude is small

Implications and next steps

Mechanisms?

- This type of technology adoption has a firm-level effect, possibly supported by the productivity channel (similar to previous firm-level studies)
- No evidence of a displacement effect or change in relative demand for skills at different levels of the wage distribution (within the adopting firm)

Next steps

- Testing the productivity (and profit) channels explicitly (productivity pass-through/rent sharing)
- Testing the role of labour market institutions by exploiting sectoral differences in collective bargaining/collective agreements
- Robustness tests: removing re-exporting firms, focusing on manufacturing only