The Impact of Automation on Inequality Across Europe

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January 3, 2021

Inequality Changes 00s-10s

- Historically, EU is known to have lower rates of inequality
- Varied experience of changes to inequality across Europe
- No consistent patterns by geography or years as a member in the EU (in regards to recent changes)

Country	Gini 2002	Gini 2014	% Chng
IT	0.237	0.274	15.379
FI	0.187	0.209	11.716
LU	0.263	0.289	9.715
CZ	0.269	0.292	8.391
NL	0.266	0.276	3.966
BE	0.206	0.207	0.663
PT	0.356	0.356	-0.232
HU	0.330	0.323	-2.040
RO	0.384	0.376	-2.082
UK	0.341	0.319	-6.326
ES	0.314	0.273	-13.110
FR	0.309	0.254	-18.016

Source: SES, Calculated by Authors

National Factors to Changes in Inequality

- Labor institutions (Malerba and Spreafico, 2014)
- Decline in union participation (Fortin and Lemieux, 1997)
- Increased financialization (Karabarbounis and Neiman, 2013)
- Technological change (D. Autor and Dorn, 2010)

Technology is changing the labor market

Main effects can be seen in two ways:

1. Wage Effect: Changes in the demand of skills
   The relative wage of non-routine cognitive skills has risen compared to routine tasks leading to an increase in inequality.
   (D. H. Autor, Levy, and Murnane, 2003, Goos and Manning, 2007, D. Autor and Dorn, 2010, Acemoglu and Zilibotti, 2001, Costinot and Vogel, 2010, Deming, 2017, Acemoglu and D. Autor, 2011)
2. Composition Effect: Changes in the demand of jobs
   Some jobs may be completely automated and therefore disappear, while other jobs may grow to complement new technologies.
   (frey2017future, goos2003mcjobs, Berman, Bound, and Griliches, 1994, berman1998implications, Machin and Van Reenen, 1998)

Our goal is to understand, what's the contribution of each effect?

Factors

We analyze changes of inequality within a country regarding characteristics:

- Individual
  Age, Gender, Education
- Firm
  Years at Firm, Enterprise Type, Size of Enterprise
- Industry
- Labor Market
  Contract Type (permanent pt/ft, fixed, apprentice, 85% pt), Union Type
- Technology
  Risk of Automation

And compare these results **across** countries.

Data

Structure of Earnings Survey

- 2002-2014 (every 4 years)
- Individual level (Employee)
- Collected by country and harmonized by EuroStat
- Hourly real wages

We harmonized industry and education category changes across years and countries

Data

Risk of Automation from Frey & Osborne 2017

- Convert US Occupations Classification (SOC) to European Occupation Classification (ESCO)
- Classify "Risk of Automation" by occupation into categories: Low ($< .25$), Medium (.25-.75), and High ($> .75$)

Decomposition Method

We follow a RIF-reg decomposition method by Firpo, Fortin and Lemieux (2018)

1. Compare wage density functions between 2 time periods

Overall change between the 2 time periods

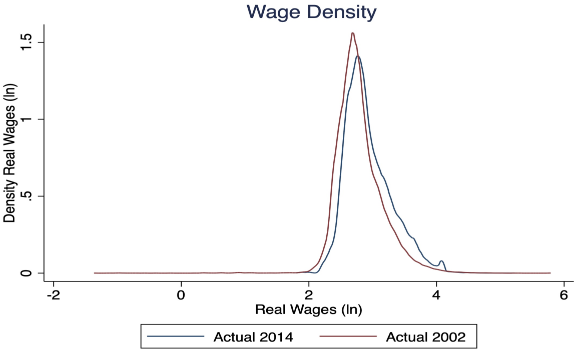


Figure: Wage Densities for Belgium

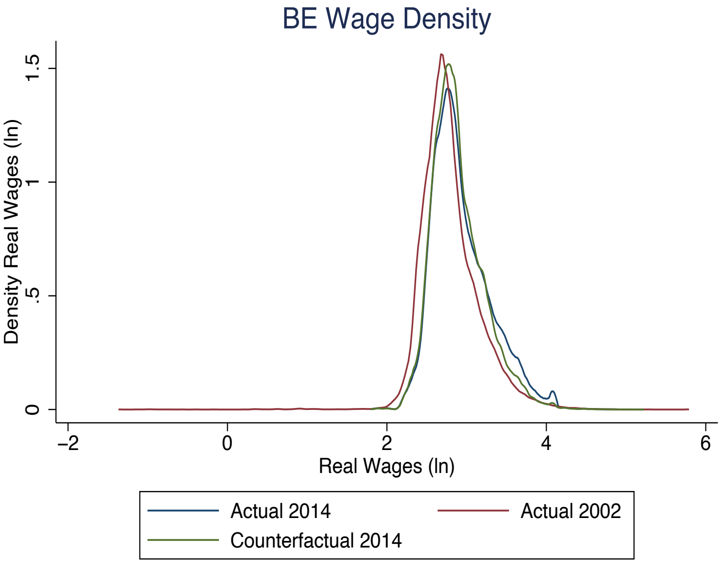
Counterfactual

2. But, how can we tell differences between wage structure and composition effects?

Create a counterfactual distribution:
Reweight the 2014 distribution with 2002 characteristics
Estimate whether an individual is in 2002:

$$
\begin{aligned}
Pr(t_i = 1|X) = \Phi(&\beta_1 age_i + \beta_2 edu_i + \beta_3 gender_i + \beta_4 ar_i \\
&+\beta_5 entyrs_i + \beta_6 enttype_i + \beta_7 entsize_i \\
&+\beta_8 emptype_i + \beta_9 union_i + \beta_{10} ind_i + \tau_i)
\end{aligned} \tag{1}
$$

Counterfactual



Counterfactual

This allows us to take differences:

1. 2002 distribution - counterfactual
   Wage Structure Effect: isolates effects of wage structure between 2002 and 2014
2. Counterfactual - 2014 distribution
   Composition Effect: isolates effects of differences in composition between 2002 and 2014

Decomposition

3. Measure differences by covariate contributions

Using RIF Regressions, we can analyze small disturbances in the data through recentered influence functions. RIF is additive so that we can see the effect that each covariate has on any statistic of interest (percentiles or Gini)

The regression coefficients provides an estimate of the change in the distributional statistic of interest (e.g. the Gini) in response to a change in the distribution of a variable that changes the unconditional average of the variable by one unit.

OB Decomposition

4. Using all of the estimates from the RIF regression, we can calculate a detailed Oaxaca-Blinder Decomposition:

$$\bar{X}^{2014}(\hat{\beta}^{2014} - \hat{\beta}^{c}) + (\bar{X}^{c} - \bar{X}^{2002})\hat{\beta}^{2002}$$

Where the first term is the wage structure effect and the latter term is the composition effects.

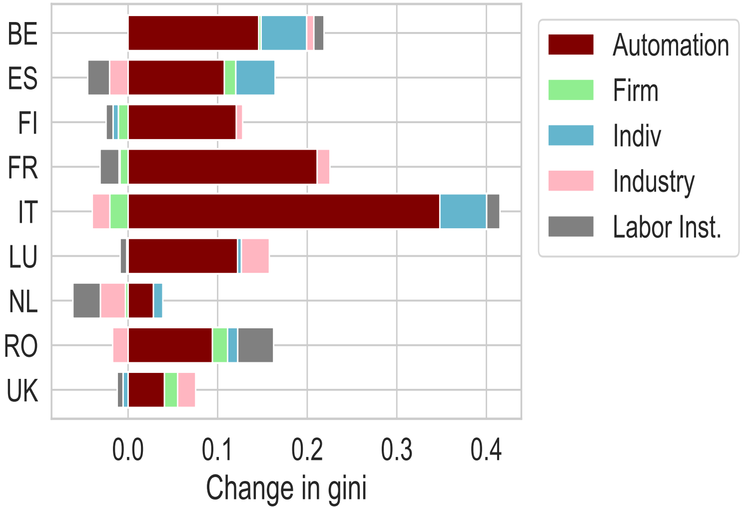
Decomposition

We do this procedure for each country:

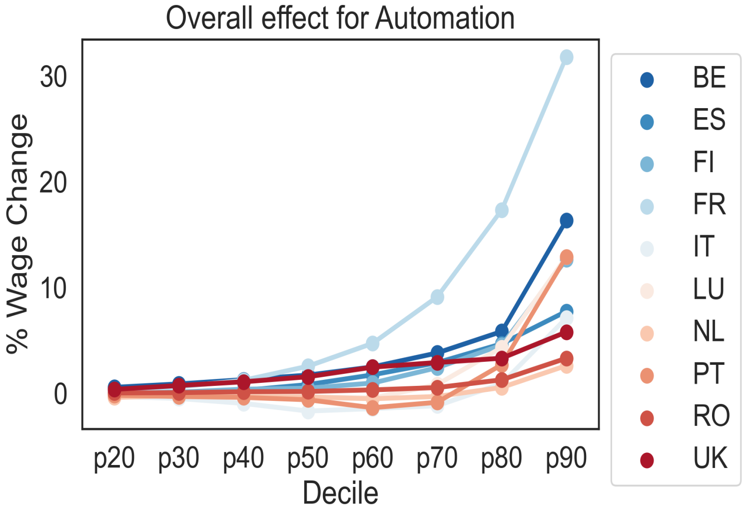
- Belgium
- Spain
- Finland
- France
- Luxembourg
- The Netherlands
- Romania
- The United Kingdom
- Italy

and decompose how individual characteristics impacted: Gini and deciles

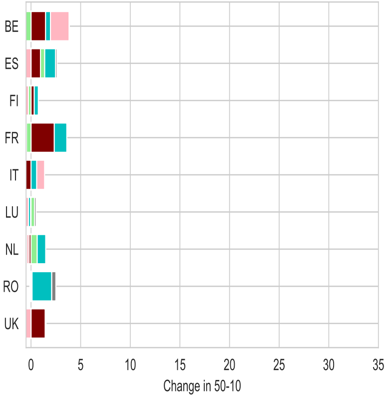
Contribution to Gini



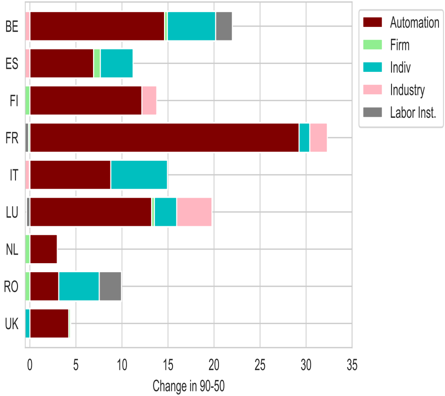
Automation's Impact



Automation's Impact

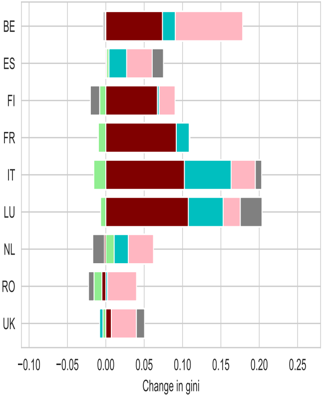


(a) Bottom Distribution

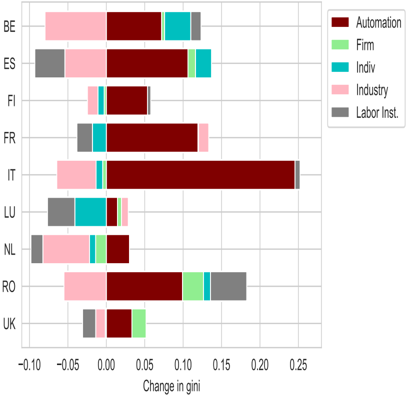


(b) Top Distribution

Automation's Impact



(c) Wage Effect



(d) Composition Effect

Automation's Impact

Jobs that are more likely to be automated tend to be more equally paid, while low automation risk jobs have higher inequality.

In the short term, as high risk automation jobs become automated workers will move to more low and medium risk jobs. However, these jobs are more unequal. Thus, this contributes to higher inequality through the composition effect.

Automation's Impact

Country	AR	2002	2014
Spain	Low AR	.282	.281
	Mid AR	.287	.282
	High AR	.254	.220
Finland	Low AR	.181	.214
	Mid AR	.160	.188
	High AR	.145	.139
France	Low AR	.297	.287
	Mid AR	.257	.310
	High AR	.232	.210
Hungary	Low AR	.251	.2333
	Mid AR	.258	.253
	High AR	.230	.258
Italy	Low AR	.350	.466
	Mid AR	.201	.310
	High AR	.216	.216

Country	AR	2002	2014
Luxembourg	Low AR	.255	.275
	Mid AR	.241	.252
	High AR	.210	.190
The Netherlands	Low AR	.202	.222
	Mid AR	.217	.258
	High AR	.214	.240
Romania	Low AR	.392	.380
	Mid AR	.366	.351
	High AR	.308	.247
United Kingdom	Low AR	.307	.299
	Mid AR	.292	.300
	High AR	.205	.214
Czech Republic	Low AR	.292	.279
	Mid AR	.235	.284
	High AR	.193	.195

Table: Gini Coefficient by AR, Country and Year

Summary

- Automation is increasing inequality all across Europe
- It explains a large portion of recent changes in inequality
- Wages growth is indeed rising much faster at the top end of the distribution
- However, wage changes is more consistently seen through the composition effect
- The driver of rising inequality through automation is the shift in the composition of jobs
- Where the share of jobs in high risk automation jobs are decreasing compared to low automation jobs

Further Consideration

- Unclear if this is a temporary effect or potential for long term increase in inequality
- Have not included impact of trade

Thank you

OB Decomposition

4. Using all of the estimates from the RIF regression, we can calculate a detailed Oaxaca-Blinder Decomposition:

$$\Delta v = \bar{X}^{2014}(\hat{\beta}^{2014} - \hat{\beta}^{c}) + (\bar{X}^{2014} - \bar{X}^{c})\hat{\beta}^{c} + \\ (\bar{X}^{c} - \bar{X}^{2002})\hat{\beta}^{2002} + \bar{X}^{c}(\hat{\beta}^{c} - \hat{\beta}^{2002})$$

Where the first two terms are the wage structure effect and the latter two terms are the composition effects.

Assuming that $(\bar{X}^{2014} - \bar{X}^{c})\hat{\beta}^{c}$ and $\bar{X}^{c}(\hat{\beta}^{c} - \hat{\beta}^{2002})$ are close to zero, we have the Classic Oaxaca-Blinder decomposition:
$\bar{X}^{1}(\hat{\beta}^{1} - \hat{\beta}^{c}) + (\bar{X}^{c} - \bar{X}^{0})\hat{\beta}^{0}$