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The Impact of Automation on Inequality across Europe

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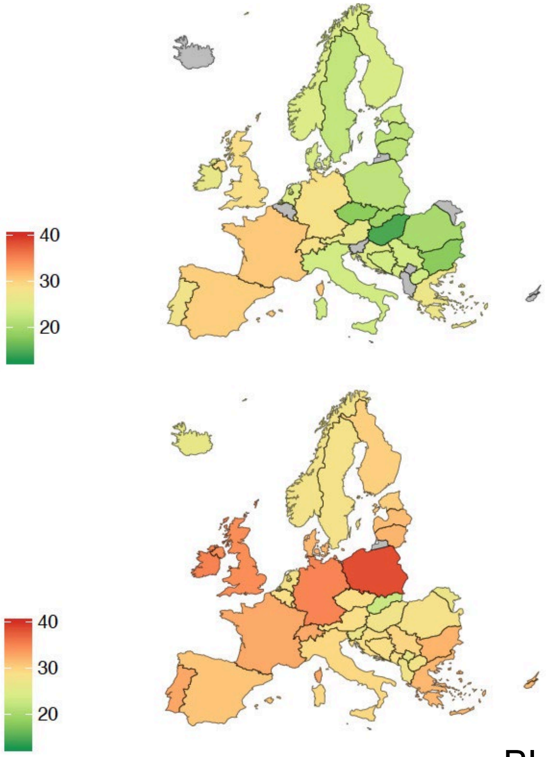
Motivation

- The EU has historically had low rates of inequality (relative to some other parts of the world)
- In the past couple of decades, inequality has been on the rise across a range of EU economies
  - Though not in all countries
  - And lots of variation across countries

Top 10% pre-tax income shares



1980

2017

Blanchett et al. 2019

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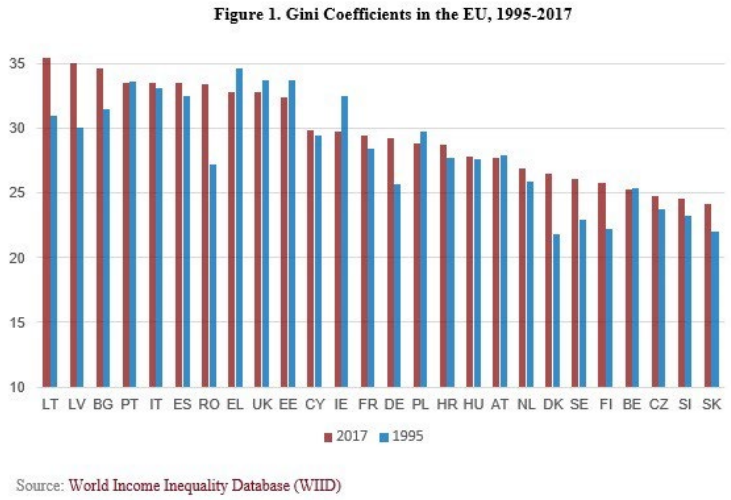
Gini Coefficients across EU Members



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Motivation

- Varying explanations for rising wage inequality across many European economies
  - Labour market institutions (collective wage bargaining, minimum wages)
  - Financialisation
  - Trade and global value chains (e.g., the rise of China)
  - Technological change (i.e., automation and robotisation)
- Increasing empirical literature highlighting the impact of automation and robotisation on labour market outcomes
  - Autor et al., 2003; Acemoglu & Restrepo, 2017; Dauth et al., 2017; Brall & Schmid, 2020
- And an emerging theoretical literature
  - Acemoglu & Restrepo, 2018; Prettner & Strulik, 2019

Motivation

- The model of Acemoglu & Restrepo (2018) identifies three potential effects of automation
  - Reduction in labour demand due to a displacement effect
  - Creates demand for labour through a productivity effect
  - May lead to the creation of new tasks
- These effects are likely to impact different workers and occupations differently
  - Relative wages of non-routine cognitive skilled workers are likely to rise relative to workers in routine tasks (a wage effect)
  - Some occupations and tasks (i.e., routine jobs) are likely to disappear, while others are likely to complement new technologies and grow (a composition effect)
- Our approach looks to shed some light on the relative importance of these two dimensions

Methodology

- The underlying approach is a standard Blinder-Oaxaca decomposition
  - Explains differences in the (mean) outcome between two groups
    - Based on a Mincer type regression
    - By decomposing differences into a wage and composition effect
      - Wage structure – holding distribution of covariates constant and varying the conditional wage structure (coefficients)
      - Composition effect – holding conditional wage structure constant and varying the distribution of covariates
  - But rather than comparing across groups (e.g., gender) we compare across time

$$\Delta w^{\mu} = \bar{X}^{2014}\left(\hat{\beta}^{2014} - \hat{\beta}^{2002}\right) + \left(\bar{X}^{2014} - \bar{X}^{2002}\right)\hat{\beta}^{2002}$$

- i.e., the mean wage gap equals a wage structure effect plus a composition effect

Methodology

- This approach is extended to allow for decomposition of distributional statistics other than the mean
- Using the Recentred Influence Function (RIF) regression decomposition approach of Firpo et al. (2018)
  - RIF regressions are commonly used to estimate unconditional quantile regression models (Firpo et al., 2009)
  - And allow one to quantify the impact of each covariate on the change in various wage inequality measures (e.g., percentile wage gaps, the Gini coefficient)
- The resulting decomposition is:

$$\Delta w^{\tau} = \bar{X}^{2014}\left(\hat{\beta}^{2014,\tau} - \hat{\beta}^{2002,\tau}\right) + (\bar{X}^{2014} - \bar{X}^{2002})\hat{\beta}^{2002,\tau}$$

  - With Δw^{τ} being the wage gap at the τth (unconditional) quantile (or some other distributional statistic, e.g., Gini, IQR, etc.)

Data

- Eurostat's Structure of Earnings Survey
- Data for the period 2002-2014 (every 4 years; also now for 2018)
- Data for 15 European countries
  - Model estimated separately for each country (computational problems)
- Individual level data (Employee)
- Dependent variable: Hourly real wages

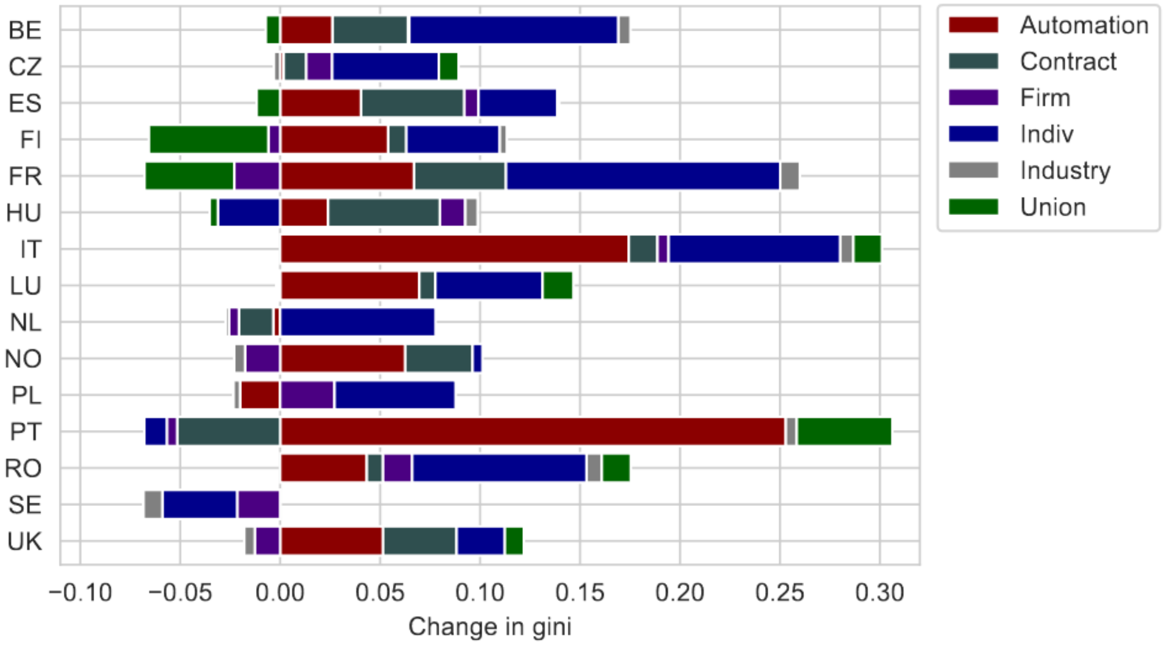
Explanatory Variables

Characteristic type	Variables
Individual level	Age, Gender, Education, Years at firm
Firm	Enterprise type, Enterprise size
Industry	Sector fixed effects
Labour markets	Union type (e.g., national, regional, local), Contract type (e.g., pt/ft)
Technology	Automation risk

Automation Risk

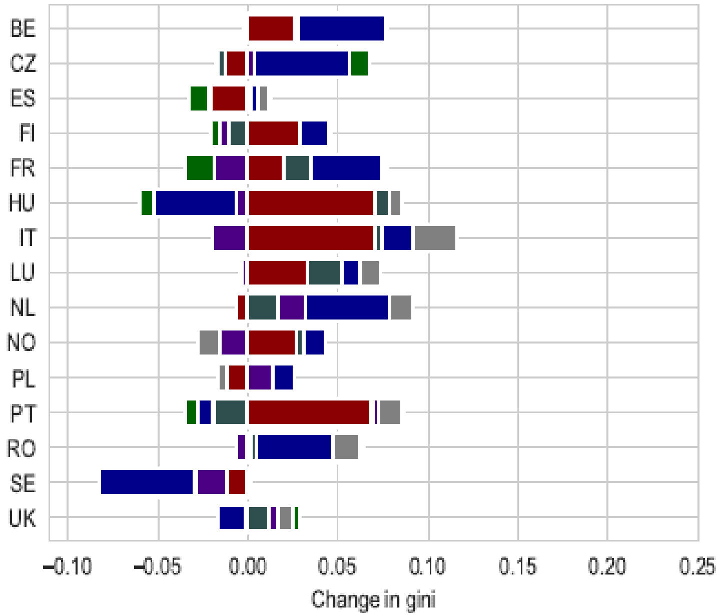
- Automation risk calculated using the approach of Frey & Osborne (2017)
  - Relate probability of automation to bottlenecks
- Convert US Occupations Classification (SOC) to European Occupation Classification (ESCO)
- Classify automation risk by occupation into three categories:
  - Low (Automation risk < 0.25)
  - Medium (0.25 < Automation risk < 0.75)
  - High (Automation risk > 0.75)
- Dummy variables for medium and high automation risk included in the RIF regressions

Results on the Gini Coefficient



- Increase in Gini observed across most (but not all) countries
- Contributions of different characteristics vary across countries
- Automation risk contributes positively to inequality in nearly all countries
- Though its relative importance varies

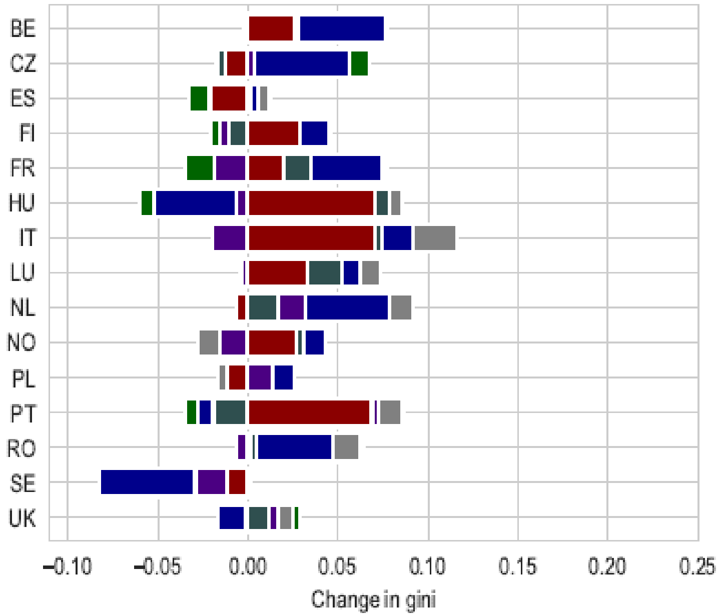
Results on the wage effect



(a) Wage Effect: Change in Gini

- In most cases, the wage effect is the weaker of the two effects
- Automation risk is a major contributor to the wage effect in most countries
- Coefficients on high automation risk in RIF regressions tend to be negative

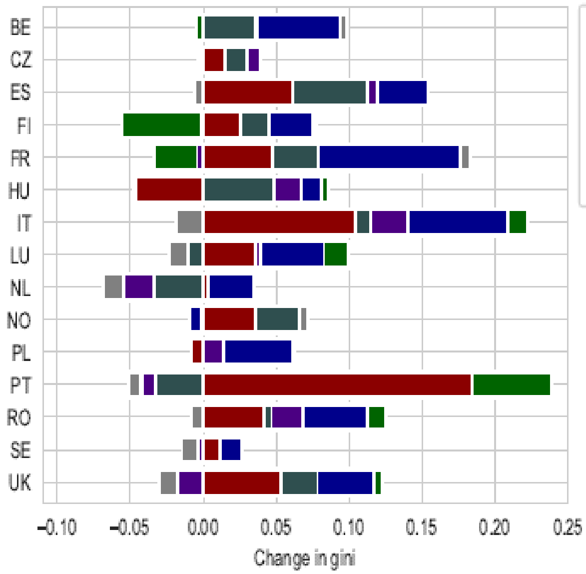
Results on the wage effect



(a) Wage Effect: Change in Gini

- Why do we obtain negative coefficients on automation risk?
  – High automation risk jobs have a more equal distribution of wages compared to low automation risk jobs (job polarisation)
  – An increase in the share of high automation risk jobs will therefore lower inequality levels
- But, these negative coefficients tend to diminish between 2002 and 2014
  – All else equal, the decline in the negative effect over time will increase inequality through the wage effect

Results on the composition effect



(b) Composition Effect: Change in Gini

- Composition effect the dominant driver of changes in the Gini
  - –Automation risk contributes positively to this term in most countries
- Given the negative coefficient on automation risk in 2002, this positive effect must be due to a decline in the share of high automation risk jobs
  - –In other words, there is a higher share of workers in low automation risk jobs and these jobs tend to have more unequal wages

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Conclusion

- Earnings inequality has risen across a range of EU countries
  - These increases are concentrated in the upper part of the earnings distribution
- Automation appears to be an important contributor to rising inequality
  - Especially in the upper part of the income distribution
  - Consistent with a routine-biased technological change argument
- Automation impacts via two effects:
  - A wage effect
    - Automation risk lowers inequality, but this negative effect has fallen over time
    - A weakening role of high automation risk jobs in reducing inequality
  - A composition effect
    - A declining share of high automation risk jobs, with the remaining jobs having more unequal wages
    - That is, automation is generating / protecting jobs that are both poorly and highly paid

Extensions

- Beyond Frey & Osborne
  - Shortcomings of the Frey & Osborne approach
  - Webb (2020) identifies exposure to robots, software and AI
- Additional dimensions
  - Role for trade and global value chains
  - Role for financialisation
- Generalisations
  - Pseudo panel methods


THANK YOU
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SHUKURIA
DANKSCHEEN
TASHAKKUR ATU
YAQHANYELAY
SUKSAMA
EKHMET
MEHRBANI
GRAZIE
BİYAN
SHUKRIA
TINGKI
BOLZÏN
MERCI
JUSPAXAR
GOZAIMASHITA
EFCHARISTO
KOMAPSUMNIDA
MAAKE
PALDIES
SPASSIBO
SNACHALHUYA
NUHUN
CHALTU
WABEEJA
MAITEKA
HUI
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